THE DETERMINANTS OF STOCK MARKET VOLATILITY: MACROECONOMIC FUNDAMENTALS AND INVESTOR SENTIMENT

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ABSTRACT

Stock market volatility is an important risk indicator of stock returns. Investors are hesitant to invest in high stock market volatility, thereby affecting the market. This warrants the need to identify possible determinants of stock market volatility. This study focuses on volatility in the Malaysian stock market. Lack of information about the causes of volatility results in inaccurate investment strategies, also affecting the ability of regulators to take measures to eradicate potential bubbles caused by irrational exuberance. The present study examines the ability of macroeconomic fundamentals and investor sentiment in predicting the volatility of the stock market. Specifically, the objectives of this thesis are: (i) to examine the predictive value of macroeconomic fundamentals on the volatility of the Malaysian stock market; (ii) to investigate the predictive value of investor sentiment on the volatility of the Malaysian stock market; and, (iii) to determine whether macroeconomic fundamentals and global financial crisis affect the predictability of investor sentiment on the volatility of the Malaysian stock market. The third research objective serves as a robustness test in determining the validity of the newly-constructed Investor Sentiment Composite Index. The period of investigation spans from 2000 to 2012, highlighting the duration of the global financial crisis.

Predictability of macroeconomic fundamentals and investor sentiment with respect to volatility of the stock market was modelled with auto-regressive distributive lags (ARDL) (p, q). Only inflation rate and money supply displayed short-run dynamics with the volatility of the Kuala Lumpur Composite Index (KLCI) during the period of study. This contradicts previous empirical research. Additionally, the newly-constructed Investor Sentiment Composite Index showed significant predictive power for the volatility of the KLCI. Investor sentiment predicted the volatility of the KLCI as early as four months in advance during the period of crisis and three months prior to event during the whole period of study. Investor sentiment retained its predictive value even after being controlled for the 2008 global financial crisis and macroeconomic fundamentals. Interestingly, it is found that investor sentiment significantly predicted the volatility of the Malaysian stock market during the global financial crisis, while macroeconomic fundamentals displayed no significant predictive value. This suggests that during crisis, extreme volatility is influenced more by non-fundamental factors, such as the irrational behaviour of investor sentiment. This provides a clearer picture to policymakers, regulators, and stock market participants in forecasting volatility, assisting in portfolio rebalancing, as well as in deciding on possible measures to avoid negative impact of excess volatility.

ABSTRAK

Ketidaktentuan harga pasaran saham adalah petunjuk risiko penting bagi pulangan saham. Pelabur akan teragak-agak untuk melabur dalam pasaran saham yang mempunyai ketidaktentuan harga yang tinggi, sekali gus menjejaskan pasaran. Ini menjamin keperluan untuk mengenalpasti penentu mungkin ketidaktentuan pasaran saham. Kajian ini memberi tumpuan kepada pergolakan dalam pasaran saham Malaysia. Kekurangan maklumat tentang punca ketidakstabilan mengakibatkan strategi pelaburan yang tidak tepat, juga mempengaruhi keupayaan pihak berkuasa mengambil langkah untuk membasmi potensi buih yang disebabkan olehnya. Kajian semasa mengkaji keupayaan asas ekonomi makro dan sentimen pelabur untuk meramalkan ketidakstabilan pasaran saham. Secara khususnya, objektif tesis ini adalah: (i) untuk mengkaji nilai ramalan asas ekonomi makro pada ketidakstabilan pasaran saham Malaysia; (ii) untuk menyiasat ramalan nilai sentimen pelabur pada ketidakstabilan pasaran saham Malaysia; dan, (iii) untuk menentukan sama ada asas-asas ekonomi makro dan krisis kewangan global menjejaskan kebolehramalan sentimen pelabur pada ketidakstabilan pasaran saham Malaysia. Objektif kajian yang ketiga berkhidmat sebagai ujian keberkesanan dalam menentukan kesahihan Indeks Komposit sentiment pelabur. Tempoh penyiasatan merentangi dari tahun 2000 hingga 2012, menonjolkan tempoh krisis kewangan global yang berlaku pada tahun 2008.

Kebolehramalan asas makro ekonomi dan sentimen pelabur terhadap ketidaktentuan pasaran saham di model dengan auto-regressive distributive lags (ARDL) (p, q). Keputusan menunjukkan bahawa kadar inflasi dan bekalan wang dipaparkan mempunyai hubungan dinamik dengan turun naik Indeks Komposit Kuala Lumpur (KLCI) di sepanjang tempoh pengajian di mana ianya bercanggah dengan kajian-kajian empirikal terdahulu. Di samping itu, Indeks Komposit sentimen pelabur menunjukkan

kuasa ramalan penting bagi ketidakstabilan KLCI. Sentimen pelabur meramalkan ketidakstabilan KLCI seawal empat bulan lebih awal semasa tempoh krisis dan tiga bulan lebih awal di dalam tempoh keseluruhan pengajian. Sentimen pelabur mengekalkan nilai ramalan walaupun selepas setelah dikawal untuk krisis kewangan global 2008 dan asas-asas ekonomi makro. Menariknya, didapati bahawa sentimen pelabur dengan ketara meramalkan ketidakstabilan pasaran saham Malaysia semasa krisis kewangan global, manakala asas ekonomi makro dipaparkan todak mempunyai nilai ramalan yang ketara. Ini menunjukkan bahawa semasa krisis, turun naik yang melampau adalah dipengaruhi oleh faktor-faktor bukan asas seperti tingkah-laku rasional sentimen pelabur. Ini memberi gambaran yang lebih jelas kepada penggubal dasar, pengawal selia pasaran saham dan peserta pasaran saham dalam ramalan lebihan ketidaktentuan, membantu dalam pengimbangan portfolio, serta dalam membuat keputusan mengenai langkah-langkah perlu untuk mengelakkan kesan negatif daripada lebihan ketidaktentuan.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

KLCI	Kuala Lumpur Composite Index
NYSE	New York Stock Exchange
CPI	Consumer Price Index
BLR	Base Lending Rate
IPI	Industrial Production Index
M3	Broad Money Supply
EER	Effective Exchange Rate
TURN	Stock Market Turnover
IPO	Initial Public Offering
RIPO	Return of Initial Public Offering
NIPO	Number of Initial Public Offering
CSI	Consumer Sentiment Index
EMH	Efficient Market Hypothesis
MPT	Modern Portfolio Theory
ISCI	Investor Sentiment Composite Index
ISCIC	The Cleaner Index of Investor Sentiment

CHAPTER 1: INTRODUCTION

1.1 Research Background

Stock Market Volatility

Researchers have debated stock market anomalies over past decades. Excessive volatility of stock prices cannot be explained by standard value-efficient market models (Shiller, 1981; 1987; 1990). The theory of excess volatility, according to Shiller, proposes that people act irrationally on the information they receive, thus creating unexplained volatility in the stock market. Understanding of stock volatility is crucial in the equity market. It causes uncertainty that may hinder investors' decision to buy or sell stock. This affects growth of the equity market, and of the economy as a whole. Lack of information about the causes of volatility may cause inaccurate investment strategies, which also affects the formulation of appropriate measures of regulation.

Numerous attempts account for the drivers of this anomalous performance. Some researchers have tried to link this anomaly with macroeconomic fundamentals (Davis and Kutan, 2003; Officer, 1973; Schwert, 1989), while others associate stock market volatility with human emotion. According to Martin (2011), the most lethal determinant to stock market volatility is human emotion and bias. Martin (2011) suggests that greed and fear can also cause investors to accelerate in the buying and selling of stocks, thus resulting in short-term volatility. This is supported by studies by Lee, Jiang and Indro (2002) and Verma and Verma (2007), who found investor sentiment to be a significant driver of the volatility of Standard and Poor's 500 (S&P 500) returns in the New York Stock Exchange (NYSE).

There is also a growing body of research where behavioural finance explains stock price volatility during different market conditions. For instance, Law (2006) and Angabini and Wasiuzzaman (2010) found higher volatility in the KLCI during the 1998 Asian financial crisis and the 2008 global financial crisis. Such a scenario can be explained by the overreaction of investor sentiment during the crisis periods, as implied by the findings of Zakaria and Shamsuddin (2012). The question that arises is whether Malaysian investors are manipulated and influenced by non-fundamental news in their decision making. Stock market participants tend to make irrational investment decisions based on a number of behavioural biases; for instance, relying on personal experiences in their investment decision making, hoping to obtain abnormal returns. It is reported that irrational behaviour was intense during uncertain economic conditions, such as during the 2008 global financial crisis. The contagious effect of the global financial crisis on the Malaysian stock market is discussed in the next section.

The Global Financial Crisis (2008) and its Effect on the Malaysian Stock Market

During the global stock market crash of 2007-2008, the Morgan Stanley Capital International (MSCI) world index experienced a free-fall to approximately half of its index price from peak to trough, and the contagion effect on emerging markets was inevitable, which fell further by imitating the behaviour of developed markets (Figure 1.1). By early 2009, the MSCI Emerging Markets Index had fallen by 66% from peak to trough, plunging by the same magnitude as the stock markets of developed countries. Regardless of sound fundamental economic conditions, Malaysia was not spared from the slide, as the stock market dropped by 67% from its peak in the third quarter of 2007. It is not surprising, then, that academics and practitioners associate the behaviour of local stock markets with regional and global stock markets. The 2008 contagion was widespread. For instance, the economic crisis in the United States during late 2007 caused abrupt major shifts in world stock market indices. This gives credence to the popular cliché, “if the US sneezes, the whole world catches a cold” in the context of economic or financial adversities.

In February 2008, the KLCI steadily trended up to a high of 1436 points when the US stock market had experienced a fierce downtrend in the third quarter of 2007. However, in October 2008, the KLCI plunged below its support level at 1000 points, and continued to dwindle. Despite reports of stable fundamental economic factors such as GDP, the Malaysian stock market appeared to be unfavourably affected by the crisis. From late 2007 until January 2009, Malaysian investors appeared to respond in a panicked manner, as shown in Figure 1.1.

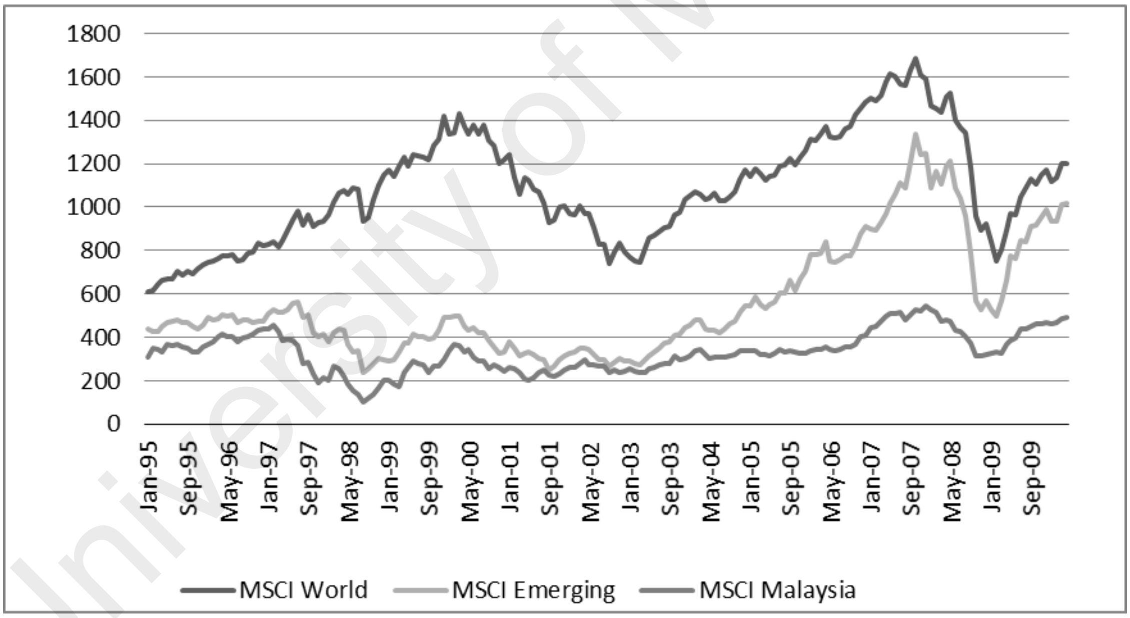


Figure 1.1 Movement of indices (Source: Bloomberg International)

The Malaysian stock market seemed to be oblivious to assurances from the government that this fundamentally strong country would not be affected by the US financial crisis. The negative sentiments were so strong that they induced panic selling from local investors and foreign investors in all Asian countries, including Malaysia. With the idea that the impact would surface in the economy of these countries, the stock market undoubtedly received the preliminary impact due to infectious sentiment all around the globe. This was exacerbated by processes of globalisation and efficient communication technology, which lead to fluctuations in index during crisis. Therefore, it is crucial to investigate whether fluctuations in the Malaysian stock market during this crisis were explicated by macroeconomic fundamentals or non-fundamental factors, or maybe an incorporation of both. This understanding may assist policymakers, regulators, and stock market participants formulate appropriate tools and policies to implement during critical economic conditions.

Theoretical Background

One of the three assumptions of the theory of an efficient market is that competing participants analyse and value their investment rationally. The initial belief was that trade based on anything but fundamental factors would fall prey to rational arbitrageurs, and would eventually be forced out of the market. Fama (1965) and Friedman (1953) wrote that irrational investors would divert stock prices from their fundamental value only in the short-term. Consequently, rational investors would then arbitrage away the differences by trading against the irrational ones, bringing the price back to fundamental values and creating a counter-effect on market prices.

Studies such as those by Long, Shleifer, Summers and Waldmann (1991), Shleifer and Summers (1990), Shleifer and Vishny (1997) have questioned the validity of the aforementioned counter-effect as a plausible tool to predict stock price movements and volatility. Investors tend to imitate the acts or judgements of other investors, or simply make decisions based on market rumours (Shiller, 1984). According to these studies, an important reason why arbitrage is limited is because of the unpredictability of changes in investor sentiment. Therefore, due to the extreme behaviour of investor sentiment, arbitrageurs who bet against mispricing would face the risk of extreme prices that move even farther away from fundamental values. Other studies have recognised that investor sentiment may be a significant factor contributing to market-wide asset-pricing processes. Evidence suggests that investors do not trade rationally, yet they still outperform the market most of the time.

In January 2000, Daniel Kahneman, a well-known psychologist, gave a presentation at a conference on behavioural finance at a prestigious university in the U.S. His talk revolved around the psychology of the stock market arguing that stock market participants are swayed by the powerful emotions of extreme nervousness and anxiety. He talked about how beliefs, thoughts, moods, and sometimes irrational emotions form the moulds to asset-pricing. In short, the market is seen to closely resemble stereotypical individual investors, which creates an illusion of intentionality and continuity by making sense of the past. This statement is interesting in view of traditional theories of asset-pricing, whereby the stock market is accepted as a mechanical entity that behaves rationally as a result of fundamental effects – a theory that embraces rationality and rejects any non-fundamental ideas proposed by behaviourists.

There is, however, a good deal of empirical evidence on asset-pricing that goes against the tenets of the efficient market hypothesis and suggests that the behaviour of investors should not be undermined. These studies argue that irrational investment decisions should not be treated as anomalies, as modern theories of finance typically do. Investor sentiment influences the price-formation of stocks, suggesting that investor psychology should be given more attention in current studies and should not be overlooked or ignored (Brown and Cliff, 2004; 2005).

Therefore, investor sentiment and psychology has been increasingly acknowledged by practitioners in stock analyses[1]. Attempts have been made to explain the behaviour of asset prices from the perspective of investor psychology. Researchers began diverting their focus from the modern portfolio theory (MPT) to a behavioural paradigm in explaining stock market prices. To a certain extent, this is due to progressive empirical evidence that the erratic movement of the stock market could not be explained by fundamental factors. Shiller (1981) argued that the stock market exhibited persistent, excessive volatilities, which could not be explained by market fundamentals alone. He proposed that, due to sociological and psychological beliefs, investor reactions exert a greater influence on the market than fundamental factors. Meanwhile, other researchers postulate that the stock market behaviour may be influenced by non-fundamental factors such as noise, feedback trading, and irrational expectations (Campbell and Shiller, 1988; Lee, 1998). Thus, psychological models incorporating investor behaviour and the influence of beliefs on asset-pricing began to evolve.

The assumption of rationality under the Efficient Market Hypothesis (EMH) paradigm seemed far too perfect to be applied to real contexts. Evidence from studies in psychology suggests that humans possess psychological biases that prevent them from being rational and "error-free" in making investment decisions. In evaluating risky investments, investors do not consider final wealth; instead, they make evaluations based on the possibility of gain and loss relative to some reference point (Kahneman and Riepe, 1998).

The foundation of investor sentiment lies in the theory of noise-trading introduced by Black (1986), and later refined by Trueman (1988). Both authors assert that noise-

[1] Despite abundant scholarly work addressing the existence of investor sentiment and irrational investor behaviour in the financial world, the behavioural finance paradigm was not fully accepted until just a decade ago.

trading no longer exists as a temporary shock or short-term movement in asset prices, as EMH had advocated. They argued that noise-trading exists as it plays an important role in providing liquidity, particularly in riskier assets. In the behavioural finance paradigm, the price of stocks held by noise traders is always affected by the sentiments of noise traders, as long as there is a limit to arbitrage as observed when it is risky and costly to trade (Lee, Shleifer, and Thaler, 1991; De Long et al., 1991). Barberis, Shleifer and Vishny (1998) developed a model of how investors formed beliefs and produced under-reaction and overreaction towards news. This empirical evidence demonstrates the importance of investor sentiment in asset-pricing in real-world investment decisions.

Investor Sentiment and International Stock Markets

The co-movement of financial markets has been the focus of interest among practitioners and academics since the development of global equity markets. Stock markets follow each other due to the efficiency of information and news travelling across the world. The existence of satellite television and the internet makes it possible for information including sentiments of investors to travel at an unprecedented speed (Shiller, 2000; Tetlock, 2007).

Most studies were concentrated on the United States and other developed stock markets; however, studies have started to discover the effect on emerging stock markets. Two research papers are worth citing in this thesis in the broader perspective of world issues. The most recent is Baker et al. (2012), which studied the effect of investor sentiment in six major developed countries: Canada, France, Germany, Japan, the United Kingdom, and the United States of America. They examined how investor sentiment spread among those countries. These studies are discussed further in Chapter Two.

1.2 Rationale of the Study

The main factor that warrants a study on the Malaysian stock market is the absence of participation from market-makers in controlling stock exchange prices. Market specialists in developed stock markets such as the NYSE have existed for decades. These designated market-makers function to enhance liquidity in the stock market, which is then expected to bring about stabilisation of short-term price fluctuations through appropriate bid and ask quotes. Since the establishment of Bursa Malaysia in 1964, trading of equities in Malaysia is structured as an order-driven market, which had never been under the influence of a structured and systematic liquidity provider. This could account for the unexplained volatility as mentioned by Shiller (1987). It is also noteworthy that retail investor investors serve as liquidity suppliers among selected stocks, so their net demands for stocks normally conflict with the movement of the overall market (Kumar and Lee, 2006). This behaviour is in line with the observation by Kaniel, Saar and Titman (2008) that when institutional buying (selling) pressure pushed prices up (down), retail investors incline to provide liquidity. These factors provide a strong motivation for the need to study the effect of irrational investor sentiment on Bursa Malaysia in the asset-pricing context.

Another major incentive to focus on Malaysian stock market volatility is found in previous findings of extreme volatility that the Malaysian stock market experienced during the 1997 Asian financial crisis, as well as during the 2008 global financial crisis (Law, 2006). Evidence of fluctuation in the MSCI Malaysia index that closely followed MSCI world index is shown in Figure 1.1. However, the present study focuses on the recent global financial crisis, rather than the 1997 Asian financial crisis, since different financial mechanisms and policies for the sustainability of the system were imposed during these two periods. For instance, postliminary to the 1997 Asian crisis, the

Malaysian government had introduced numerous policies to improve financial sustainability and stimulate economic growth. However, from 2001 onwards, these capital controls were removed and capital began to flow back into the economy (Lim and Goh, 2012). This includes, the unpegging of the Malaysian ringgit to the U.S dollar, imposed to stem massive capital outflow in 1998. Hence, the efficiency of the Malaysian stock market was expected to have improved; and Malaysia was expected to weather further financial crises in the new millennium. Thus, the effect of irrational investor behaviour on the stock market may not be as prevalent as it was in 1997.

The causes of extreme volatility observed in emerging markets, however, have been inconclusive to date. For instance, while Schwert (1989) found the effect of inflation and money growth to be weak for U.S market volatility, Beltratti and Morana (2006) found interest rate and money growth to have affected the S&P 500 volatility. On a larger sample, Davis and Keaton (2003) found a marginal effect of inflation in 13 developed and developing countries. Locally, interest rate affected Malaysian stock market volatility (Zakaria and Shamsuddin, 2012). These inconclusive findings motivated other researchers to divert their attention from fundamental drivers to the incorporation of non-fundamental drivers in explaining the volatile stock market.

Research on anomalies includes the size effect, weekend effect, value-stocks effect, and momentum effect. These are not only researched in Unites States stock markets, but have gained popularity in Malaysia as well. Local researchers have for long noted the financial anomaly in Malaysian stock prices. Two decades ago, Wong, Neoh, Lee and Thong (1990) documented the Chinese New Year and Eid celebration effects, apart from the widely researched January effect from 1970-1985. Their findings are supported by Ahmad and Hussain (2001) and Yakob, Beal and Delpachitra (2005), which observed the manifestation of the Chinese New Year and January effect respectively. Additionally, the day-of-the-effect anomaly was significant over the study period with regard to pre- and post-1998 Asian financial crisis (Chia, Liew and Wafa, 2006). This was corroborated in a more recent study from 2000-2006 (Lim, Ho and Dollery, 2007). The firm size effect has also been a subject of research, as Shaharudin and Hon (2009) found the relationship between small firm size and stock returns of Bursa Malaysia to be controlled by macroeconomic factors.

Apart from these, another interesting behavioural anomaly of the Malaysian stock market to catch the interest of researchers is investor overreaction to stock prices over the news. Ahmad and Hussain (2001), Ali, Md Nassir, Hassan and Zainal Abidin (2010), Ali, Ahmad and Anusakumar (2011) conducted their studies under the overreaction hypothesis (Bondt and Thaler, 2007) and found significant overreaction of investors over stock prices during the Chinese New Year season, economic crises, and during political events. Hameed and Ting (2000), Lai (2002), Arifin and Power (1996) documented that the phenomena of overreaction and momentum exist in the local stock market, and that these are the manifestation of irrational investor behaviour. Being among the largest financial markets in the world, Asia has consistently demonstrated the evidence of psychological biases (anecdotal, theoretical, and empirical) as a significant factor influencing investment decisions (Ali, Ahmad and Anusakumar, 2011; Charitou, Vafeas and Zachariades, 2005). Collective-oriented societies can cause individuals to be overconfident, and this is observed as one of the biases that Asian cultures tend to hold in a socially collective paradigm (Kim and Nofsinger, 2008).

1.3 Problem Statement

Anomalies (Ali, Nasir, Hassan and Abidin, 2010; Shaharudin and Hon, 2009) and unexplained volatility during crises (Angabini and Wasiuzzaman, 2010; Zakaria and Shamsuddin, 2012) are persistent in the Malaysian stock market. Their persistence renders the theory of efficient market impertinent to the equity market. Hence, there arises the possibility of investors beating the stock market and earning abnormal returns by adopting non-fundamental analyses. If extreme volatility during a crisis is not controlled, it may lead to further crisis, which is likely to affect the economy on a larger scale. The evidence of macroeconomic fundamentals as drivers of the volatile market has been inconclusive as different researchers reported different findings and impacts of economic variables in different countries[2]. This suggests that there are factors other than fundamental factors that may explain the movement of stock prices. Therefore, if macroeconomic fundamentals inadequately explain stock market volatility, what could be the other significant factors that influence the fluctuations?

Recent research literature seems to rely on empirical findings to verify the behaviour of stock prices in the local stock market. Researchers have diverted their attention towards the evidence of psychological factors. A model of investor sentiment developed by Barberis, Shleifer and Vishny (1998) explains investor sentiment in terms of under-reaction and overreaction to bad and good news regarding stock prices. Overreaction and investor sentiment connect in ways that affect stock prices (Ahmad and Hussain, 2001; Ali et al., 2010; 2011). Thus there is a need to further explore the impact of investor sentiment in decision making in the Malaysian stock market.

However, the measurement of investor sentiment remains controversial. Definitions and measurement are still a major issue of contention in analysing the effect of investor

[2] Beltratti and Morana, 2002; Diebold and Yilmaz, 2008; Engle, Ghysels and Sohn, 2013; Rahman, Sidek and Tafri, 2009

sentiment on the equity market. These uncertainties cause difficulties for international fund managers and investors in determining an optimum investment strategy on fundamental grounds. Therefore, the essence of the strategy is to find a reliable and applicable measure of investor sentiment relevance in the stock market.

To reiterate, this thesis addresses the inconclusive findings of the effect of macroeconomic fundamentals in extreme volatility in the stock market and the unavailability of a perfect measure for investor sentiment to examine the contribution of non-fundamental factor to the stock market volatility. This causes difficulty for practitioners and investors in the allocation of financial resources as part of their investment decision making. Hence, to assist the facilitation of decision making in equity markets, it is crucial to determine the drivers of stock market volatility. This leads to the development of the following objectives for the present research.

1.4 Research Objectives

This research incorporates behavioural finance in the traditional asset-pricing theory. Evidence from this thesis is not intended to discard the efficient market theory, but to complement our understanding of stock market behaviour by incorporating an alternative explanation from the perspective of behavioural finance. The importance of behavioural factors is evident in a statement by Shefrin (2002, p. 53), “Now sentiment is a very important concept in Behavioural Finance. A consistent theme in this book is that sentiment is a reflection of heuristic driven bias.” Shefrin (2002) also writes that fundamental analysts and technicians have addressed these issues to determine the right investment strategies to outperform aggregate stock market participants.

Since market-wide behaviours in stock market conditions are involved, especially in emerging economies, the concepts of investor sentiment and anecdotal theory will be clearly defined. This study does not ignore the contribution of macroeconomic fundamentals towards explaining the volatility of the stock market. In fact, the possible relationship between macroeconomic fundamentals and volatility of the Malaysian stock market will also be examined. This study also seeks to contribute to research literature in the area of methodology that has not been applied previously.

Drawing upon the previous discussion, the objectives of this study are:

1) To examine the predictive value of macroeconomic fundamentals on the volatility of the Malaysian stock market
2) To investigate the predictive value of investor sentiment on the volatility of the Malaysian stock market
3) To determine whether macroeconomic fundamentals and a global financial crisis affect the predictability of investor sentiment on the volatility of the Malaysian stock market

The period of investigation is from 2000-2012. Nevertheless, further investigation during the period of the global financial crisis is also conducted to investigate whether fundamental and non-fundamental variables influenced the volatility of the stock market returns during crisis. Additionally, an Investor Sentiment Composite Index relevant to the Malaysian stock market will be constructed. Research objective 3 examined whether the newly-constructed Investor Sentiment Composite Index would be able to sustain its predictive value with the inclusion of macroeconomic fundamentals and the global financial crisis as control variables. This step will serve as a robustness test of the newly-constructed index. These research objectives are expected to respond to a number of research questions as outlined in Section 1.5. Section 1.6 briefly presents the significance and contribution of the thesis.

1.5 Significance and Contribution of the Study

This thesis extends the literature on investor sentiment in emerging stock markets, which has received little research attention, although there are compelling factors contributing to financial anomalies on excess volatilities. Emerging markets have higher conditional volatility and larger price changes than mature stock markets (Bekaert and Harvey, 2003; Santis, 1997). The behaviour of prices in these stock markets contributed more than 75% per annum of returns as noted by Lesmond (2005). Additionally, Shefrin (2002) asserted that excess volatility could be explained by trader overreaction, either to news or to its absence. As a result, an increasing number of research is published on behavioural finance and its potential in explaining stock price volatility and anomalies. The relationships between many other market behaviours and decision attributes on volatility are well-documented by Thaler (1991, 1993) and Brock and Wood (1995). As cited by Olsen (1998), Schwartz (1988) writes that financial economists seem to have agreed that volatility of security prices and trading volume should vary with discrepancies in investor opinion, which remain unexplained by standard theories of modern finance.

The main issue to address here is the notion that investor sentiment is expected to have a more significant effect on the stock markets of emerging economies compared to its effect on developed countries regarding returns and volatility. Therefore, the insight to investor sentiment is essential as this determines whether risk premium to noise-trader risk or investor sentiment risk of all stocks should be demanded, thus support the controversial behavioural theories that predict the effect of irrational sentiments of investors on price levels (Brown and Cliff, 2004, 2005; Brown, 1999).

The findings of this thesis are significant to asset-pricing theory; in particular, to the assumption of irrational investors in behavioural finance in explaining stock market inefficiencies. The findings of this thesis are expected to help disentangle rational from behavioural theories of asset-pricing; the former do not acknowledge the role of investor sentiment, and rule out any relationship between asset-pricing and sentiment. This study examines stock market volatility, particularly excess volatility as posited by Shiller (1989). These are important issues in the study of investment, since they bring into view a holistic picture of the fundamental and technical processes of the market, millions of dollars of which are lost in attempts to beat the market and earn abnormal returns.

This study contributes to research on emerging markets in South-East Asia, with a focus on the Malaysian stock market. In light of the evidence suggested by Morck et al. (2000), poor property protection rights by the government in emerging economies deter risk arbitrage, and create space for noise traders (Long, Shleifer, Summers, and Waldmann, 1990). This study extends the Investor Sentiment Composite Index developed by Baker and Wurgler, (2006; 2007), by adapting it to the Malaysian stock market with two additional proxies – advance decline ratios (Brown and Cliff, 2004; 2005) and the consumer sentiment index (Hsu, Lin, and Wu, 2011; Schmeling, 2009). Each proxy is tested and results are compared prior to determining the measurement for investor sentiment.

This study makes methodological contributions with the application of the ARDL model in searching for significant and parsimonious relationships between the variables. Thus far, this model has not been used widely in the context of studies reacted to stock market volatility. This model is eminent when variables are from different order integrations, i.e., I(0) and I(1). Finally, the extension of this study covers the effect of the 2008 financial crisis that impacted global stock markets, including Malaysia. All contributions as suggested by the findings in this thesis are evidence that fundamental and non-fundamental factors play an important role in predicting the volatility of the Malaysian stock market.

1.6 Organisation of the Thesis

Chapter One provides a brief background of the study, states the problem statement, the research objectives and research questions. Chapter Two describes the theories – including traditional emerging-market hypotheses and behavioural finance theories – that form the basis of this thesis. Chapter Three outlines the empirical evidence that either supports or questions the validity of investor sentiment measurement and its application to emerging stock markets. This chapter also presents the research framework and hypotheses of the study. Chapter Four presents the methodology and explains the nature of data sources for empirical tests.

Empirical findings are the focus of Chapter Five. This chapter tests the hypotheses in order to answer the research questions; it thus includes descriptive and multivariate analyses, i.e., the discussion of results. Finally, Chapter Six provides a summary of the thesis, and consolidates empirical findings from Chapter Five. A discussion that integrates all research objectives is provided, including implications for understanding of stock market volatility. We also discuss theoretical contributions of the study. The chapter ends with a section on the limitations of the study, and recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter begins with a discussion of the efficient market hypothesis. As findings on macroeconomic fundamentals as determinants of stock market volatility have proven to be inconclusive globally, more researchers have attempted to shift to a paradigm in contrast to traditional theories of finance. Of these, behavioural finance has started to be recently accepted; it underlines the importance of human behaviour in asset pricing theory. One of the theories that underlies behavioural finance is the noise trader theory. This chapter will thoroughly discuss the theory proposed by Black (1986) and Trueman (1988); it is the cornerstone of every article in investor sentiment literature. Described as stock traders whose decisions to buy, sell, or hold are irrational and erratic, noise traders in financial markets may cause prices and risk levels to deviate from expected levels even if all other traders are rational.

The chapter then continues with a discussion of relevant articles on the development of the noise trader model. The model explains the contribution of sentiment in anomalies found in asset pricing and the efficient market. The proxies adopted to measure investor sentiment are discussed by taking into account observation of investor sentiment in different countries from recent studies. The chapter continues with empirical evidence on the association of fundamental and non-fundamental factors in stock market returns and volatility. Section 2.2 will thoroughly discuss the early acceptance of behavioural finance.

2.2 The Efficient Market Hypothesis (EMH)

The origins of the EMH can be traced as far back as the pioneering theoretical contributions of Bachelier (1900) and of the Nobel Laureate Samuelson (1965) (Davis and Etheridge, 2011). They postulated that speculative prices were generated by a random process whereby successive price changes were essentially random in character, and that price of previous trading did not influence the price of current returns. Since Fama published his work in 1965 and contrived the idea of EMH, a number of studies were carried out to investigate the behaviour of stock prices based on EMH. Fama (1965) examined the correlation between current and previous returns on stocks, using a sample of 30 stocks from Dow Jones industrial average. He found statistically significant serial correlation coefficients, but weak economic significance, as they were too small to compensate for the transaction costs incurred. In 1970, Fama provided a comprehensive review of the theory and evidence of market efficiency. He proceeded to empirical investigation to support the development of the theory in efficient market.

Numerous studies have also examined the effect of the announcements of company-specific events, including mergers and acquisitions, seasoned equity offerings, spin-offs, and dividends and earnings on stock market behaviour to determine whether the market reacted according to the postulations of the efficient market hypothesis. Fama, Fisher, Jensen, and Roll (1969) examined the stock price reaction around stock splits, as many investors believed that stock splits resembled good news following the increase of stocks dividend. However, Fama et al. (1969) observed no evidence of abnormal stock price performance. This suggested that investors would not be able to earn abnormal profits by purchasing stocks on the split date. The evidence was therefore consistent with the efficient market hypothesis.

Meanwhile, Keown and Pinkerton (1981) determined the stock price changes of target companies around the announcement of takeover attempts. The findings revealed a small upward shift in prices prior to the announcement, suggesting that some information may have leaked out. However, stock price changes were, on average, close to zero after the announcement. These results are also consistent with the efficient market hypothesis, since they suggest that the effect of the information was absorbed almost immediately after the announcement, and that stocks immediately returned to their fundamental values.

In traditional finance, there is typically no opportunity for the existence of non-fundamental determinants of stock market volatility. Such theories generally ignore or assume away the behavioural paradigm, arguing that the effect of sub-optimal trading behaviours such as consideration of non-fundamental values is instantaneously removed with the intervention of rational arbitrageurs. Briefly, traditional finance revolves around two basic properties which imply the lack of prolonged arbitrage opportunities when both are taken together, namely: informational efficient financial markets, and rational market participants.

On the foundation of traditional financial economics, EMH upholds that all relevant information on the principal security's fundamental value should reflect in the prices of financial assets. Supposing there are no frictions, the security's fundamental value – expressed by the discounted amount of future cash flows – must reflect in its price. Mathematically, subject to all available information at a given time, the price of a particular security of portfolio, P_t, should be equal to the projected future cash flow and its investment risk. This is represented as:

$$P_t = Et[Pt{+}1jIt] \qquad (1)$$

The efficient market hypothesis posits that a security's optimal forecast should be equal to its price. This indicates that unexpected activities in the stock market are initiated by the fundamental value's P_{t+1} new information (Fama, 1965). The EMH then resumes that fundamental value encompasses two main components, namely, a predictable and an unpredictable component:

$$P_{t+1} = P_t + u_t \tag{2}$$

where u_t signifies the estimated error, and must not be correlated with any information accessed at time t; otherwise all available information would not be taken into account (Shiller, 2003). P_t and u_t must not be correlated with each other as the price P_t is also information. Hence, in the decision-making process, the market efficiency paradigm assumes that individuals would generally behave rationally, taking into account all available information. Rational investors would instantaneously respond to new information on security, which leaves no room for returns that originate from information signal.

According to traditional finance, the forces of self-interest and arbitrage will immediately eliminate the effect of irrational investors and risk-free profit from the market. Nevertheless, although financial markets are practically imperfect, market mispricing may be difficult to take advantage of (Shleifer, 2000). This is due to trading costs, which include information costs, transaction costs, and financing costs incurred. However, this notion was opposed by Shleifer and Vishny (1997), who observed prolonged mispricing due to unexploited arbitrage opportunities even after fundamental risks and transaction costs were taken into consideration. This so-called anomaly would still be difficult to explain from the viewpoint of traditional finance. Moreover, financial anomalies – such as Initial Public Offerings (IPOs) under-pricing and close-ended fund discount – observed from empirical studies evidence inefficiency of the stock market.

EMH triggered a number of empirical studies that attempt to determine whether financial markets are efficient, and, if so, the extent of their information processing efficiency. Most of the early empirical studies on EMH were conducted using US data, because US markets are probably the most developed capital markets in the world, providing an effective testing ground for EMH. Nevertheless, interest in the efficiency of smaller stock markets outside the United States rapidly increased in the 1970s. Despite a range of well-known works on EMH, findings have been far from unanimous, especially in recent years where market inefficiencies or anomalies have been documented and remain unexplained by EMH. This raises the question of whether EMH is still relevant; it also questions the implications of these findings to both academicians and practitioners.

One of the approaches to explaining these anomalies is to resort to behavioural explanations that relax the assumption of strict rationality from traditional theories of finance. Recently, an increasing number of studies have turned to the behavioural finance paradigm, which explores deviance from strict rationality and how this deviance may influence market effects, prices of assets, and other investor behaviour. Behavioural finance also offers a more flexible approach to explain financial anomalies such as excess volatility with regard to investor sentiment.

2.3 Fundamental Determinants of Stock Market Volatility

Introduced and formulated by Ross (1976) and Roll and Ross (1980), arbitrage pricing theory extends the capital asset pricing model by incorporating variables from macroeconomic fundamentals; they were able to prove that these variables were risk-priced factors in generating asset returns. Based on this, more researchers attempted to link all classes of macroeconomic variables (inflation rate, money supply, GDP growth rate, and industrial output) to the pricing of investment portfolio. Failure to observe any significant predictive value in macroeconomic variables to portfolio returns put the basic intuition of the APT at stake. The theory questions whether systematic variability or systematic beta alone affects expected returns – which is the central theme of modern asset pricing theory. Arbitrage pricing theory links specific macroeconomic fundamental variables in explaining global stock market volatility. If these fundamental links prove to be significant, the theory may well be relevant to modern asset pricing. We shall now discuss previous empirical research that sought to examine macroeconomic fundamental determinants of stock market volatility.

Extreme volatilities in the stock market have been observed during major economic crises such as the 1997 Asian financial crisis and the 2008 global financial crisis. The most popular explanatory factor in stock volatility studies is macroeconomic variables. Kraft and Kraft (1977) examined the causal relationship between stock prices and money supply, rate of change of money supply, corporate interest rate, and a measure of risk. The data were in monthly frequency for the period of 1955 to 1974. Results revealed no causal relationship between stock prices and the variables under study. This was consistent with EMH – that the stock market is an efficient entity, and that any attempt to explain stock prices based on historical and current information is futile.

Two decades later, Schwert (1989) found that macroeconomic variables inadequately predicted volatility of stock returns. His study adopted a measure of stock market volatility introduced by French, Schwert and Stambaugh (1987), whereby standard deviation and variances were calculated from monthly stock returns on data from 1928-1987. Macroeconomic variables were represented by inflation and money base growth.

The findings reported that relationship between stock market volatility and inflation money growth was weak.

Davis and Kutan (2003) extended Schwert's (1989) study by examining the impact of inflation and real output on stock volatility in 13 developed and industrialised countries. The volatility measured with generalised autoregressive conditional heteroscedasticity [GARCH (1,1)] and exponential generalized autoregressive conditional heteroskedastic [EGARCH (1,1)] models was consistent with Schwert (1989); the predictive power of macroeconomic volatilities over stock market volatilities was marginal. However, output movement appeared to have predictive power over volatility in three among the sample countries. Meanwhile, inflation had significant predictive power over a three-month horizon in four among the sample countries. Beltratti and Morana (2002) opposed the widely applied GARCH (p,q) effect in modelling volatility. They contended that unrealistic high projections of future conditional volatility on high current volatility was due to the method of extrapolation that GARCH uses. Banking on an innovated strategy, Beltratti and Morana (2002) supported Schwert's (1989) original study in terms of the significance of inflation in predicting the volatility of S&P 500 returns.

In the context of Malaysia, Zakaria and Shamsuddin (2012) examined the effect of five common macroeconomic variables (interest rate, inflation, money supply rate, GDP, exchange rate) on volatility in KLCI for the period of study from 2000-2012. Their results were far from conclusive; they observed inconsistent behaviours with the application of different causal relationship models. The volatility of variables was measured with GARCH (1,1) on monthly data at KLCI. Their study, however, had issues in accuracy. The data they chose to represent exchange rate was invalid due to the pegging of the Malaysian ringgit to the US dollar from 1998 to 2005. During this period, the Malaysian ringgit to US dollar exchange rate showed no movement to represent volatility. Secondly, the application of the ARCH family effect to measure volatility in KLCI was inappropriate, since the clustering effect from monthly data seems subtle compared to daily data (Beltratti and Morana, 2002; Brailsford and Faff, 1996). Hence, their results suffer from multiple data biases.

To reiterate, the determinants of stock market volatility have been of significant interest among researchers. One of the motivations has been to test the efficient market hypothesis initially supported by Kraft and Kraft (1977). The other motivation was to test the validity of the arbitrage pricing theory, which explains the pricing of stock returns by the movement of macroeconomic fundamentals. Nonetheless, more recent studies (Beltratti and Morana, 2002; Humpe and Macmillan, 2009) that employ different measures for volatility have managed to recognise the relationship between macroeconomic fundamentals and volatility of stock returns. These findings shed light on the level of informational efficiency among markets in developed or developing countries. Given that the link between fundamentals and stock market volatility is uncertain, it supports neither EMH nor APT. Researcher interest has thus turned towards a different paradigm of stock market volatility. More researchers have started to explore the possibility of non-fundamental variables in explaining stock market volatility – investor sentiment is widely thought to be one such variable.

2.4 Investor Sentiment

Shleifer (2000) highlights that despite embracing the new paradigm, researchers still found loopholes in understanding investor behaviour, and that more research needed to be carried out. Part of the reason for the loopholes was that psychological evidence regarding errors of judgement in financial economics is still under-developed. The relevance of psychological biases to investor sentiment is still open to debate.

Baker and Nofsinger (2002) claim that investors could suffer from optimism bias, one of the precursors of overconfidence described as a common bias in judgement by Kahneman and Riepe (1998). The investment decision-maker thus relies on intuition, which plays a crucial role in most decision-making processes. This means that optimism leads to possible asymmetric outcomes in the investment process.

There are three ways in which optimism affects investors. First, optimistic investors tend to be less critical in making investment decisions, since most are biased towards optimism. Secondly, optimists are likely to ignore unpleasant information about their stocks, and to underestimate the probability of bad products over which they have no control – behaviour that is analogous to cognitive dissonance. Finally, optimism leads to the illusion of control, meaning that optimists overestimate their ability to manage luck, thereby underestimating and misperceiving the role of chance. Psychological studies have found these biases to be systematic and robust (Barber, Odean, and Zhu, 2009). Individual investors are found not only to incline more towards biases than the general population, but in some circumstances they tend to display speculation, confidence and herding behaviours (Barberis and Thaler, 2003).

A particularly crucial deliberation for rational arbitrageurs is the presence of other investors who may be inclined to external sentiment. These "noise traders" may trade based on sentiment rather than reliable information, as they are not fully rational. Having no access to insider information, noise traders are likely trade on noisy sentiment, which they believe is reliable information that gives them advantage in the trading of shares (Black, 1986). Accordingly, since their trades are not randomly distributed across assets, noise traders tend to underestimate expected returns in some periods and overestimate them in other periods. Hence, their anticipations of asset returns are highly sensitive to changes in sentiment.

Noise traders believe that returns may not revert to the mean, and that they tend to even greater expansion in the future. A possible justification for the existence of unexploited arbitrage opportunities is that this risk is normally borne by other market participants (De Long et al., 1990). In contrast to the conventional view that stock return co-movements are influenced by changes in fundamental value or discount rate influence, an instantaneous consequence of the noise trader model is that co-movement of returns can also be encouraged by the correlated activities of unexpected noise traders. If all traders trade randomly, their trades revoke each other's, hence aggregate demand shifts do not exist. As sentiment is correlated across these noise traders, risk cannot easily be diversified away. Due to the unpredictability of noise traders, rational arbitrageurs acquire limits to arbitrage; noise trading, thus, is a persistent risk. Trading strategies based on pseudo-signals (e.g., advice of brokers and investment gurus, noise, and correlated popular models) result in notable aggregate demand shifts. This means that besides macroeconomic variables and standard risk factors, the interaction of unpredictable noise traders and sophisticated arbitrageurs may also determine stock prices. The noise trader theory acknowledges the presence of investor sentiment. However, apart from making the association between irrational noise traders and other market participants, the noise trader model is yet to be clearly delineate as to what kind of effect sentiment has and how it operates in the market – especially since general noise also affects market outcomes.

2.5 Non-fundamental Determinants of Stock Market Volatility

The importance of non-fundamental determinants of stock market volatility has been addressed in a theoretical paper by Shefrin and Statman (1994). Behavioural capital asset theory is based on the notion that in an inefficient market, noise traders' judgement errors also drive volatility in addition to fundamentals. This is through distortion of the mean-variance efficient frontier, creating abnormal returns to particular securities, resulting in abnormal returns and market beta (Chopra, Lakonishok, and Ritter, 1992). According to this theory, noise trader actions are more a manifestation of the joint failure of a single driver property, rather than just a collection of unrelated phenomena. As a structured theory, it provides specific functions, forms for the mean-variance efficient frontier, and an analogue to the standard capital asset pricing model (CAPM), thus extending standard pricing models to the case of price inefficiency.

Economists view sentiment in two ways. The first is based on traditional asset pricing theories, which contend that rational assessment of expected future payoffs contributes to the movement of asset prices (Fama, 1965; 1970). This view disregards the role of investor sentiment, as price changes are reflected by the appearance of external news about future cash flows and interest rates. The second economic view of sentiment stems from the paradigm of behavioural finance, which argues that market outcomes and asset prices in equilibrium are significantly distorted by investor sentiment. The noise trader model postulates that investor sentiment leads to deviation of asset prices away from the expectations of an efficient market. These two views create room for the possibility of factors other than fundamentals that may influence the volatility of stock returns.

2.5.1 The Development of Investor Sentiment

Black (1986) states that, “Noise is what makes our observations imperfect.” It thus affects the way we observe the world. This challenges the dominance of traditional finance under the efficient market hypothesis after three decades of its introduction. Black (1986) introduced the idea of a type of trading that presumes noise as pure information about the stock market. He noted that noise trading is crucial in providing liquidity in the shares of individual firms, and that it is essential in correcting the prices of costly trades among information traders. Information traders are supposedly keen on taking advantage of the inefficient market, and would initiate takeovers, mergers, and other restructuring with the expectation of abnormal profits. However, this act of arbitraging would gradually move prices back to fundamental values. Nevertheless, noise has not left the macro economy untouched. Black (1986) wrote about the role of uncertainty or noise in affecting markets with cost helping shift physical and human resources within and between sectors. This concept calls upon the involvement of other researchers in laying a solid foundation of behavioural finance in asset pricing.

The next significant study of the era is by Trueman (1988), who extended Black’s (1986) model in an attempt to explain why fund managers would rationally engage in noise trading, even though they are informed of risks in investment. Trueman demonstrated that fund managers manipulated the perception of investors towards the observed total amount of trading. They banked on the fact that inexperienced investors would have difficulty distinguishing information based trading from non-information based trading. Therefore, fund managers tended to increase their involvement in noise trading in order to increase fund turnover, indirectly giving out signals of optimism regarding fund performance. As a result, inexperienced investors would increase their position in the fund with the belief that they were making good decisions in the investment.

Despite recognising the role of noise trading in the market, conventional finance scholars tend to ignore the contribution of the behavioural paradigm in regard to asset pricing. For instance, Fama (1965) and Friedman (1953), who stand by EMH, acknowledge the existence of the noise trader; however, they posit that noise traders are usually met by rational investors who arbitrage the price deviation back to fundamental values. Therefore, this effect is not sustainable in the long run. Fama (1998) asserted that market anomalies were only a result of chance that was likely to exist due to methodological imperfections. He emphasised the relevance of EMH in asset pricing, despite the existence of evidence undermining it.

De Long et al. (1990) challenge the tenets of EMH by holding on to the notion that the effect of noise trading is not simply eliminated by arbitraging. In the real world, there are risks of noise traders not reverting to the mean in the future. Noise trading becomes phenomenal as arbitrageurs are unable to liquidate their positions due to limits on arbitrage. When this model was applied to explain financial market anomalies, it was proposed as an optimal pricing strategy, taking into account noise trader risk, as well as identifying the possible role of long-term investors in stabilising asset prices. The model acknowledges the existence of two distinct types of investors in their pricing function, namely, sophisticated and noise traders. It assumes that opinions of noise traders are unpredictable, therefore arbitrageurs are required to bear the risk of more extreme misperceptions in the future. Indeed, in some cases, professional arbitrageurs behave similar to noise traders as opposed to investors who trade based on fundamentals. This is because arbitrageurs are willing to spend a fortune to analyse and predict pseudo-signals in technical analysis in an attempt to beat the market, expecting to thus earn abnormal returns.

The above details are supported by Shleifer and Summers (1990), who explain that there is a sharp distinction between arbitrageurs and other stock market participants in asset pricing. Like other non-traditional finance theorists, Shleifer and Summers (1990) disregard theoretical models with perfect arbitrage due to their impracticability. They believe that noise traders do not appear as random traders in financial markets, as posited by the efficient market hypothesis. Instead, noise traders are “pseudo-signal” followers, as Black (1986) suggests. These pseudo-signal based trading strategies are highly correlated to aggregate demand shifts. The involvement of trend-chasers overrides the mistakes of over-reacting and under-reacting investors to news in financial markets, creating a stronger mispricing of assets (Alpert and Raiffa, 1982; Tversky and Kahneman, 1982). As a result of prolonged aggregate demand shifts, higher risk-bearing stocks are expected to consistently reward noise traders. By and large, Shleifer and Summers (1990) models and extrapolates the role of arbitrageurs in exploiting the behaviour of noise traders in the expectation of outperforming the market.

However, attempts of recognising the existence of noise traders have not stopped since. De Long et al. (1991) extend the earlier model by further examining the survival of noise traders in the long run. Rather than examining the level of expected returns, De Long et al. (1991) study long-term effects on wealth distribution between noise traders and rational arbitrageurs. Using one-period and multi-period infinite horizon models, they were able to show that noise traders earned higher expected returns than rational investors for a large set of possible misperceptions. However, due to several limitations, noise traders were not allowed to affect prices. This contradicts the whole general view of studies in favour of the noise trader theory. With this limitation, noise traders are not only able to earn higher returns, but to dominate the market in the long run in terms of wealth. The De Long study thus does not provide support for the significance of investor sentiment on the price formation of stocks in the financial markets. It does, however, provide an idea of the effect noise traders have on their own long-term wealth.

Motivated by prior empirical research regarding investors' under- and over-reacting to news, Barberis et al. (1998) developed a model that reasonably challenges the efficient market hypothesis. They proposed a parsimonious model, suggesting that investors make decisions under the influence of specific uncertainties – that firms' earnings move between the reverting mean and the trend that earnings develop. This psychological model was motivated by two important phenomena: conservatism (Edwards, 1968), and the representativeness heuristic (Tversky and Kahneman, 1982). Based on the bottom-up approach with artificial datasets of earnings and prices, the results were consistent with expected under- and over-reaction patterns. However, there were signs of asymmetries where average returns following positive earnings were greater than average returns following a negative shock. The foregoing are among the few early studies pertaining to the noise trader theory. Since then, other studies have attempted to empirically investigate this topic. The next section of this chapter discusses the various definitions of investor sentiment.

2.5.2 Definitions of Investor Sentiment

As opposed to unanimity regarding the concept of investor sentiment among market practitioners, there is little consensus on the definition of the concept among researchers. In financial markets, it is well-known that investor sentiment plays a role in the stock market. Investor sentiment is recognised as the expectations or confidence of individual investors and other market participants (analysts, traders, fund managers) regarding current and future stock prices.

The term investor sentiment itself has a range of meanings, and is used in different ways by practitioners, the media, and academic researchers (Baker and Wurgler, 2007; Barberis et al., 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Shefrin, 2007). For instance, while some researchers refer to investor sentiment as the inclination to trade on noise rather than information (Baker and Wurgler, 2007; Black, 1986; De Long et al., 1990; Shleifer and Vishny, 1997), others refer to it as excessive pessimism (bearish) or optimism (bullish) among investors towards the stock market's current and future prices or preference of favourable and unfavourable outcomes (Brown and Cliff, 2004, 2005; Shefrin, 2007). Available definitions of investor sentiment vary from ambiguous statements about investors' mistakes in investment decision-making to model-specific psychological biases (Shefrin, 2007; 2008). Researchers thus define it as excessive optimism where the number of favourable outcomes compared to unfavourable ones is often overestimated.

Meanwhile Antoniou, Doukas, and Subrahmanyam (2012) broadly define sentiment as whether an individual has extraneous sources of unreasonable optimism or pessimism about a given situation. Baker and Wurgler (2006) and Brown and Cliff (2004) share similar definitions; they relate investor sentiment to investors' expectations relative to the norm, distinguishing between bullish and bearish sentiments. Baker and Wurgler (2007) go a little further by focusing sentiment effects on cross-sectional data, and define investor sentiment as the tendency to speculate when relative demand for speculative investments is driven by sentiment. This behaviour causes cross-sectional effects, even if the forces of arbitrage are the same across stocks.

The definitions lead numerous studies to focus on industries on the stock market that are specifically associated with irrational investor behaviour. Most definitions take into account theoretical concepts in behavioural finance – such as noise trader, overconfidence, optimism, heuristics, biases, and conservatism – which are incorporated into models that explain how investors form beliefs. These models, however, involve insights into the psychological behaviour of investors, which is discussed in the next section.

For the purpose of this thesis, definitions from previous researchers are refined in order to take into account possible psychological biases of investors: optimism, overconfidence, and noise. Therefore, we broadly define sentiment as the optimism or pessimism of investors, and their inclination to trade on noise as information towards current or future market positions. In this context, as active participants of the stock market, irrational investors collectively behave to induce significant stock market movement.

2.5.3 The Measurement of Investor Sentiment

Attempts to measure investor sentiment have been an encouraging aspect of research, partly due to recent historical events, and partly owing to empirical puzzles that seem to defy traditional theories of market efficiency. The term "sentiment" itself can be variously interpreted, depending on context. For instance, while some researchers may define sentiment as analogous to investor optimism (Wang, 2001), others define it in terms of dominant risk desires (Persaud, 1996). Researchers are even more in dispute regarding the measurement of sentiment. Dozens of different measures of sentiment have been proposed, ranging from direct measures such as surveys with professional market analysts to indirect measures such as financial data or stock prices and number of shares. Several proxies of investor sentiment have been used by past researchers, including surveys, market liquidity, IPOs, close-ended fund discounts, equity shares in new issues, dividend premium, and insider trading.

Surveys

Currently, there are a number of surveys, each claiming to be the tool closest to capturing investor sentiment. These surveys seek to explore whether investors are rational, such as fund managers and professional traders; or irrational, and prone to making investment judgement based on noise, rumours, or past experience (the familiarity heuristic). Survey-based sentiment indices vary from consumer confidence indices, which are available for most developed markets and a small number of emerging markets, generally surveyed on perceptions of the country's economy (Fisher and Statman, 2003; Lemmon and Portniaguina, 2006; Schmeling, 2009). These surveys may also be specific – for instance, the stock market confidence index was specifically constructed by the economist Robert Shiller to capture investor confidence since 1989, and was targeted at professional and individual investors who represent two crucial kinds of participants in stock markets.

A study by Fisher and Statman (2000) employed a proxy for sentiment from three different surveys to differentiate the behaviours of three groups of investors and their effect on stock returns. They concluded that the sentiments of Wall Street strategists – who represent a large group of investors – were significantly unrelated to the sentiments of newsletter writers, who represent the medium group of investors and individual investors. The survey based direct measures required several assumptions as the detection of sentiment-prone traders, which was conditional on the response biases from survey participants. For example, respondents with limited knowledge of financial markets were most unlikely to answer questions accurately. This makes them the best candidates to study representative bias. Baker and Wurgler (2006) corroborate this by highlighting that economists tend to treat surveys with doubt due to the potential gap between how respondents responded to the question and their actual behaviour. The schedule released for these indicators was often either in monthly or quarterly frequency, making them less timely than indirect proxies. These surveys were thus more difficult to help capture market-wide and company-level sentiment.

Another popular measure is the consumer sentiment index (CSI). CSI is designed to measure the degree of optimism among consumers regarding the general state of the economy. It measures how confident they are regarding the stability of their current income, in order to determine their spending habits. If the consumer sentiment index is higher, consumers make more purchases, which eventually boosts economic expansion. If confidence is lower, consumers tend to save more than they spend, which tends to stimulate contraction of the economy.

It is widely assumed that the CSI, also known as consumer confidence index (CCI) in some countries, is a good indicator of household consumption behaviour in economic studies (Batchelor and Dua, 1998; Easaw and Ghoshray, 2008; Nadenichek, 2007). Historically, studies have applied the consumer sentiment index from as far back as 1968, when Katona undertook pioneering research on the effect of consumer sentiment on household consumption behaviour. He argued that consumer sentiment represents households' motivation to consume, and that it conflicts with their ability to purchase, which is associated with their income and overall economic health.

Market Liquidity

Market liquidity is another proxy of investor sentiment. Over the decades, high market liquidity has been considered a symptom for over-valuation (Baker and Stein, 2004). This model relies on two sets of assumptions: first, the existence of short sales constraints, and second, the existence of irrational overconfident investors, who tend to overestimate the relative precision of stock returns from their private signals. Both assumptions lower the price impact of trades, hence generally boosting liquidity. Liquidity can also predict future returns when its shocks have a positive correlation with return shocks, as suggested by Amihud (2002). Retail investors in a market with short-sale constraints are likely to participate in trading stocks only when they are optimistic; this increases the trading volume of selected stocks. On the contrary, during market downturn and when investors are pessimists, they tend to shun away from participating in the market due to high costs of transaction and restrictions on short-selling. Generally, this also affects the turnover of the broad market. An abnormally liquid stock market is one in which pricing is influenced by irrational investors, at best representing investor sentiment. However, measuring stock market liquidity has been an issue for emerging stock markets. Market turnover, the ubiquitous and simple construct of liquidity measure, seems to have failed to account for liquidity effects in emerging markets. Volume-based liquidity measures for emerging markets are mostly aggravated by trends and outliers, posing a challenge to researchers in their analyses (Bekaert, Harvey, and Lundblad, 2007; Lesmond, 2005).

Another standard proxy for estimating liquidity is the bid-ask spread, which defines the price impact measure. Bid-and-ask spread, a widely used measure of liquidity on developed stock markets, also has limited applicability on emerging stock markets due to the lack of intraday trading data. These limitations, coupled with uncertainties surrounding liquidity estimation in emerging stock markets led researchers (Amihud, 2002; Bekaert et al., 2007; Lesmond, 2005) to test other proxies, such as market turnover, on a set of emerging countries. The empirical evidence indicates that the best possible measure for cross-country differences in liquidity is with the use of the price-based models of Lesmond et al. (1999) and Roll (1984). The volume-based models of Amihud (2002) and leading market turnover proxy are descending biased for illiquid stock markets, and are irrelevant as measures for emerging stock markets.

Information of Initial Public Offerings (IPOs)

The third group of proxies that associate with investor sentiment is the information on IPOs. The IPOs considered in this thesis are the number of IPOs (NIPO) and the average first day return IPO (RIPO). Relating the timing of an initial public offering to stock market sentiment is not new among researchers. Ibbotson and Jaffe (1975) and Ritter (1984) contended that IPOs come in waves, and that this could be accounted on three theoretical domains. Firstly, managers attempt to capture attractive stock prices by taking advantage of bull markets. Empirical measures of bull markets are based on current overall and predicted stock market conditions (Lucas and McDonald, 1990), current industry conditions, predicted industry conditions (Lowry, 2003), and recent historical market conditions (Ritter and Welch, 2002). In getting the most attractive offering prices, firms normally take advantage of favourable windows. Secondly, the attractiveness of the IPO market drives the timing of offering. Lowry and Schwert (2002) argue that the decision to go public may be influenced by the recent first day stock performance of other firms. Choe, Masulis, and Nanda (1993) argue that firms prefer to go public in tandem with the issuance of other good firms, which suggests that the sentiment of the issuing firms is a crucial factor to be considered prior to IPOs. Thirdly, Choe et al. (1993) and Lowry (2003) argue that firms make the decision to go public when they reach a certain stage in the business growth cycle, and need additional capital to expand.

Lucas and McDonald (1990) developed an asymmetric information model, where firms delay their equity issuance knowing that the equity is undervalued. When a bearish market places a low value on a firm that is too low, given the knowledge of the entrepreneurs, the issuance date is delayed until a more bullish market appears. Firms respond to investors' over-optimism as a window of opportunity to issue equities. This is further supported by Lee et al. (1991) and Pagano, Panetta, and Zingales (1998). The studies suggest that IPO volume is related to various forms of market irrationality.

While more studies have turned to behavioural finance to explain fluctuation in the number of IPO listings, Lowry (2003) finds investor sentiment to be one of the most important determinants of aggregate IPO volume in both statistical and economic terms. High IPO activity may follow high under-pricing, because at that particular time underwriters encourage more firms to go public, since public valuations are higher than expected. Models introduced by Cornelli, Goldreich, and Ljungqvist (2006) and Derrien (2005) suggest that the issuer and the institutional customers of an investment banker benefit from the presence of investor sentiment (noise traders). Therefore, promoting new issues was crucial to inducing sentiment investors into the market for an initial public offering (Cook, Kieschnick, and Ness, 2006). If it is carried out effectively, investment bankers are rewarded by the issuers.

However, Loughran and Ritter (2010) point out that the yearly number of IPOs issued varies from as low as two in Portugal and Poland to as high as 156 companies listed in India. With unique IPO features (such as government policies and corporate governance) and a distinguished structure in emerging capital markets, the same study reported high average initial returns of the sample IPOs in most emerging stock markets. For instance, initial returns were reported at 16.3% in the United Kingdom and 16.9% in the United States, which led to widespread under-pricing.

These factors provide a significant rationale to further investigate investor sentiment as a possible explanation of under-pricing in IPOs. Focusing mainly on the causes of IPO under-pricing, the theoretical work of Aggarwal and Rivoli (1990), Chowdhry and Sherman (1996), and Rock (1986) provides predictions with regard to the demand-performance relation. However, informed investors with superior information have the ability to distinguish between “good” and “bad” IPOs (Rock, 1986). They only subscribe to the notion that there is low demand for “bad” IPOs and high demand for “good” IPOs, which implies that higher returns during the first days of trading are exhibited by high demand IPOs. Chowdhry and Sherman (1996) also posited a positive relation between investor demand and under-pricing of IPOs, arguing that a severely under-priced IPO will attract a large number of investors who seek to exploit the resulting short run profit opportunities. Their model suggests that high demand IPOs experience a relatively large positive return on the first day of trading. However, the difference in post-issuance performance between high- and low demand IPOs occurs only in the short run.

Research on IPOs in developed stock markets is extensive, with, emerging markets having received scarce attention on the topic. However, the question of IPO volumes has received considerable attention from researchers in Asia. Issues regarding Malaysian IPOs are substantially researched by Yong (2007), Yong and Isa (2003), and Yong (1997). With respect to research on investor demand, Low and Yong (2011), Yong (2007), and Yong (2006, 2009) found a positive relationship between the over-subscription ratio and initial returns. The researchers went further by studying the cross-sections on the basis of three listing boards: the main board, the second board, and MESDAQ (Malaysian Exchange of Securities Dealing and Automated Quotation). In general, the smallest stock portfolio in MESDAQ posted the highest average over-subscription ratio. Among the variables under consideration (over-subscription ratio, number of days computed from the last day of application to the date of listing, number of initial public offering, offer size and offer price), only over-subscription ratio (measured by the difference of the offer price to opening price, and the close price on the first day of listing) was found to contribute significantly to the initial return.

It is therefore worth noting that the level of investors' demand of new issues can be associated with the under-pricing of issues. Investors whose applications are rejected during balloting sessions do not seemed to give up the shares. The only way to own the share is to acquire it through the open market on the initial day of listing; this manifests in the substantial increase of prices and initial returns. In this respect, investors' demand is linked to the over-subscription ratio, thus exerting larger first day returns of the initial public offering.

Closed-end Fund Discount

Closed-end fund discount is defined as a security's holdings of a fund's net asset value less than the fund's market price. These are investment companies that trade on stock exchanges that issue a fixed number of shares. In contrary to open-end funds, closed-end fund shares should be sold to other investors instead of being cashed for net asset value. By far, the most significant debate in literature has gathered investor sentiment-based behavioural explanations for the fund discount behaviour. One effect of the noise trader model is that assets subjected to fundamental risk may earn lower expected returns than assets subjected to noise trader risk. Relative to fundamental value, the latter tends to be under-priced (De Long et al., 1990). Since it is easy to observe the fundamental value of closed-end funds, it is also possible to see the noise trader model being verified. One possible relationship between the noise trader model and the closed-end fund discount is that investors holding such funds bear the possibility that the discount will, for instance, extend when noise traders unexpectedly become more pessimistic in the future. The assertion is that the fund's market price will be affected as long as this risk is systematic (Lee et al., 1991).

The core point is that fluctuations in the discounts correspond to random changes in the demand for closed-end funds by noise traders. There is an implicit assumption regarding noise traders in arguing that the closed-end discount could be explained by random sentiments. By definition, the link between investor sentiment, the closed-end fund puzzle, and the noise trader risk depends on identifying noise traders as small investors who hold closed-end funds. Even though there is empirical evidence that closed-end funds are disproportionately held by retail investors, there is an unclear logical association between sentiment and closed-end fund discount. Proponents argue that since closed-end funds are disproportionately held by small investors, there ought to be an inverse relationship of the closed-end fund discount proxies for investor sentiment. Specifically, changes in closed-end fund discounts should be negatively correlated with retail sentiment if decrease in closed-end fund discounts are positively correlated with asset returns held disproportionately by noise traders (Lee et al., 1991). The authors subsequently verified the claim that small firms outperform large firms when closed-end fund discount decreases. More importantly, however, the original authors validated closed-end funds as an appropriate proxy for investor sentiment by examining one financial measure with another (Qiu and Welch, 2004). Therefore, even though closed-end fund discount and the insignificant docile of asset returns could be significantly correlated, it is more likely that there is an absence of variables inducing both closed-end discount as well as assets seized disproportionately by retail investors, which was then leading the results.

Nevertheless, the closed-end fund discount is not free from a number of issues. First, it violates the law of one price. Although the discount is typically substantial, other explanations such as agency costs are equally likely to appear. Another issue is that the discount may not reflect the general market (Chen et al., 1993). Explicitly, investors who hold closed-end funds may be systematically different from general retail investors. For instance, trust accounts may hold a disproportionate amount of closed-end funds, but they may not characterise the sentiment of the marginal retail investor (Qiu and Welch, 2004). In conclusion, closed-end fund discount may not be an appropriate proxy for sentiment, since accepting it requires investor sentiment to elucidate the fund discount.

Drawn by the interest of previous research on mutual funds to explain sentiment, Neal and Wheatley (1998) examined the relationship between size premium and net mutual fund redemption, closed-end fund discount, and the ratio of odd lot sales and purchases. Using a large pool of closed-end fund data from 1933 to 1993, they successfully demonstrated evidence of predictability with regards to stock returns, which is consistent with the investor sentiment hypothesis. A positive significant relation between fund discounts and small firms was observed, consistent with Lee, Shleifer and Thaler's (1991) hypothesis that small firm stocks are dominantly held by small investors. It is thus a plausible explanation that sentiment occurs due to the participation of majority individual investors in the fund. The study also found a positive relation between net mutual fund redemption and small firm expected returns. However, they found a negative relation between net fund redemption and large firm returns, thus supporting the hypothesis of sentiment affecting size premium that was empirically validated by other researchers mentioned previously.

ARMS Index and the Advance/Decline Ratio

ARMS index is defined as the number of stocks advancing and the number of stocks declining, controlled by the volume traded. Information on the number of stocks advancing and the number of stocks declining is ubiquitously acknowledged as a reliable technical indicator often linked with stock market movement. This index was chosen as early as in the 1950s, in a study of stock market outlook by Bolton (1957) that showed a possible turnaround of the Dow Jones Industrial Index (DJIA). Another study by Landingham (1980) showed a leading positive signal of changes in the stock market direction, which is consistent with the standard technical theory for short-term trading.

While ARMS index is employed and widely discussed in technical analysis studies (Clarke and Statman, 1998; Klassen, 2005), behavioural finance has also tried to link the ratio of advancers and decliners to potential proxy for stock market sentiment. This proxy is included in the measurement of sentiment by Brown and Cliff (2004, 2005). They include the ARMS index as a popular measure of market sentiment among technical analysts. Although not directly include the ARMS index to the main conclusion of their study, their findings suggested that index is a good proxy of investor sentiment as it possesses significant correlation to the surveys.

Equity Shares in New Issues

Equity share in new issues is a broad measure of equity financing that measures all equity offerings in addition to IPOs. It is defined as the gross equity issuance divided by the total of gross long-term debt issuance and gross equity. High values of equity share signify low stock market returns; this pattern successfully reflects the shift between equity and debt to reduce the overall cost of capital in a firm (Baker and Wurgler, 2000). This pattern does not suggest that individual firms or their managers can predict prices on the market as a whole; rather, correlated managerial actions are led by correlated mispricing across firms, which then predicts correlated corrections of mispricing – more explicitly, it predicts market returns.

Dividend Premium

Dividend premium is the volatility premium that is the average market-to-book ratio of dividend payer less non-dividend payers (Baker et al., 2012; Baker and Wurgler, 2007; Baker and Wurgler, 2006). Generally, dividend-paying stocks have a predictable income stream, perceived by investors as a significant characteristic of security (Baker and Wurgler, 2006). Firms are more likely to pay dividends when they are at a premium, and less so when they are at a discount (Fama and French, 2001). Therefore, in order to decide whether or not to pay dividends, firms on the margin appear to provide the predominant sentiment for or against safety. Therefore, this proxy may well be unambiguously included to represent investor demand of selected securities.

Insider Trading

The true value of firms is normally better informed to corporate executives rather than outside investors. Legitimacies aside, mispricing of a firm may be revealed by executives' personal portfolio decisions. Therefore, insider trading patterns contain a systematic sentiment component if sentiment leads to correlated mispricing across firms (Seyhun, 1988). In a study by Baker and Wurgler (2006), insider buying displayed a significant negative correlation with both raw and orthogonalised sentiment indices, and correlated with the six underlying components in the index.

2.5.4 Investor Sentiment and Stock Returns

Previous studies yield a variety of findings with regard to the effect of investor sentiment on stock market returns. The idea that investor sentiment is proxied by newsletter writers as predictive of contrarian approach investors was opposed by the early studies of Fisher and Statman (2000) and Solt and Statman (1988). Both studies found that sentiment did not predict returns, as they found no significant relations in the sample from 1965. Studies progressively carried out using various approaches and methods have also resulted in inconclusive findings.

Fisher and Statman (2000) found a negative relationship between Wall Street strategists (categorised as large investors) and individual investors with future stock returns. In line with Neal and Wheatley (1998) and other researchers, studies that examine the effect of sentiment on cross-sectional stock returns seem to have found some significant effect. The data were obtained from newsletters and surveys of three different sources to distinguish small, medium and large-sized investors. The sentiment of small investors follows the performance of small capitalisation stock rather than large capitalisation stock. Lee et al. (1991) found that the sentiment of individual investors had a higher correlation with large-sized stock returns as compared to smaller capitalisation stocks. Lee et al. (1991) report an interesting ancillary finding on individual investor's stock allocation decision; they found a significant relationship between monthly change in individual investor sentiment and monthly change in stock allocation in portfolios. This suggests that individual investors do in fact make wise decisions in stock allocations contributed by their own sentiment.

Lee et al. (2002) tested De Long, Shleifer, Summers and Waldman's (1990) model on data from the DJIA, S&P 500, and Nasdaq. The Investor's Intelligence Sentiment Index was adopted as a proxy for investor sentiment. A return-generating model was proposed to explicitly test the impact of noise trader risk, both on the formation of conditional volatility as well as expected return. Results showed that a shift in sentiment had an asymmetric impact on conditional volatility. Increase in the magnitude of bullish sentiment would increase the volatility of future returns, which resulted in higher future excess returns. These findings are consistent with Brown and Cliff's (2004) findings. Other studies find that regardless of the type of noise trader risk measurement used, a shift in sentiment had a significant impact on excess returns. Results indicate a significant positive correlation between excess returns and changes in sentiment for all indices regardless of portfolio sizes. Although the results are consistent with Fisher and Statman (2000), they seem to contradict the conventional view that noise trader risk sentiment only affects small stocks (Lee et al., 1991) and that the effect is across-the-board.

A comprehensive study by Brown and Cliff (2004) employed direct (survey data) as well as indirect proxies (advance decline ratios, share interest, and the classical closed-end fund discounts) of investor sentiment. Both types of measures were examined to determine their ability to predict returns. Preliminary results found a strong relation between the two approaches with regard to investor sentiment. Applying a vector autoregressive (VAR) framework to examine these measures in predicting returns, findings revealed that changes in survey and composite measures were highly correlated with contemporaneous market returns. However, only uni-directional relationship was observed in the system where market returns appeared to vividly cause future changes in sentiment and not vice versa. The study divided the sample into two groups to distinguish between institutional and individual sentiment. It revealed the existence of individual as well as institutional sentiment. The findings rejected the conventional wisdom that sentiment is primarily an individual investor driven phenomenon that only affects small stocks. Brown and Cliff's (2004) study is, therefore, one of the most relevant studies in supporting the approach used in the present thesis, since we treat individual as well as institutional investors as groups exhibiting collective behaviour.

In a subsequent study, Brown and Cliff (2005) tested the direct relation between sentiment level and stock prices deviation from fundamental values and the long-term effect of sentiment on stock returns. A direct proxy of sentiment was used where data were collected from surveys provided by Investor's Intelligence (II), which tracked 130 market newsletter writers who reported bullish, bearish, or neutral expectations of future stock market movement. Consistent with their previous study, findings revealed that even though sentiment was strongly correlated with contemporaneous market returns, it was of no use in predicting subsequent near-term returns. Their results are consistent with Solt and Statman (1988) and Fisher and Statman (2000), who conclude that writers of newsletters tend to be trend-chasers due to the strong correlation of past returns with sentiments; and that investor sentiment has little predictive power over smaller sized stock returns.

2.5.5 Investor Sentiment and the International Market

Studies that examine the effect of investor sentiment on stock markets in emerging countries are scarce. Only two studies note the importance of examining this effect in the international market – one of these being the prominent study by Baker et al. (2012). Another study on a larger international sample examines industrialised countries, including three major world economies (the Unites States of America, the United Kingdom, and Japan) (Schmeling, 2009). However, each of the studies offered two different approaches in defining investor sentiment and proxies of measurement. Well-known for their composite sentiment index, Baker et al. (2012) explore the effect of investor sentiment on six countries: Canada, France, Germany, Japan, the United Kingdom, and the United States. They do so by introducing two different types of sentiment index: a country-specific index ("local index"), and a "total index", representing the average composite index of all countries in the sample.

Meanwhile, Schmeling (2009) emphasises on adapting the generalised consumer confidence index, which is widely used by researchers in the area of investor sentiment (Fisher and Statman, 2003; Lemmon and Portniaguina, 2006). These researchers regard the index as a direct measure of investor sentiment. They observed significant investor sentiment effects on stock returns across all countries. Baker et al.'s (2012) findings were consistent with Baker and Wurgler (2006) with cross-sectional analysis, in which there was a higher sentiment effect on stocks that were difficult to arbitrage and value, such as growth stocks, distressed stocks, small and high return volatility stocks. On the contrary, Schmeling (2009) found that the predictive power of sentiment was more pronounced for short- and medium-term horizons of one to six months as compared to longer periods.

Schmeling (2009) extends that the sentiment effect is higher in countries that have the propensity to practice herd-like behaviour on their investment decisions, i.e., countries with less market integrity and inefficient regulatory institutions, as hypothesised by Chui, Titman and Wei (2010). Both studies justify the significance of studying the effects of investor sentiment in parts of the world other than the U.S. We see, then, that evidence from developed stock markets cannot superficially be applied to markets in emerging economies; nor can the presumption that irrational investors move the stock market in general be applied superficially. This is because culture, efficiency of information, and government intervention in the financial system play an important part in explaining the sentiment-relation part of emerging stock markets in those countries.

2.5.5 Investor Sentiment and Volatility

Research interest on excess volatility started as early as the 1980s since the discovery of the earliest anomaly in the stock market (Shiller, 1987). There is, in fact, an abundance of discussion on the inconsistencies of the efficient market model for the aggregate stock market. To stock market observers, the anomalies imply that changes in prices occur for no fundamental reason at all; instead, they occur as a result of situations coined as animal spirit, sunspot, or simply mass psychology.

Financial economists seem to agree that security-priced volatility and trading volume must co-move with the divergence of investor opinion, i.e., investor sentiment (Schwartz, 1988). However, the paradigm of behavioural finance could add potential explanatory value to the existence of excessive volatility in stock prices (Olsen, 1998). The fact that volatility of security prices and trading volume varies directly with discrepancies in investor opinion remains unexplainable by traditional theories of finance without calling upon the concept of asymmetrical information. However, in widely-traded securities public markets where asymmetries are likely to be negligible, it seems implausible that differential information among investors can create the kind of discrepancies of opinion to account for the many instances of high share price volatility observed in reality. Behavioural finance motivates the present thesis to try to relate volatility with investor sentiment as the main objective.

One of the earliest studies (Brown, 1999) was motivated by the well-known noise trader model introduced by De Long et al. (1990). The findings supported the DSSW theory that irrational investors ‘acting in concert’ on a noisy signal can influence asset prices and generate additional volatility. Volatility in this sense is the volatility estimated based on daily prices of closed-end funds and on data collected for the American Association of Individual Investors (AAII) sentiment survey as the direct measure of investor sentiment. The result supported the hypothesis that there is a significant positive relationship between abnormal levels of investor sentiment and closed-end fund volatility. The most surprising finding was that overall trading volume was not affected by investor sentiment. This finding suggests that fundamental-based investors succumb to noise traders when sentiment is strong. Apparently, noise traders do not enter the market together with rational investors when sentiment is unusually bullish or bearish. They observed that while the number of trades increased, trading volume remained unchanged. The findings therefore helped explain the noticeable impact of noise traders on volatility.

Replicating the same notable model developed by De Long et al. (1990), Lee et al. (2002) and Verma and Verma (2007) attempted to associate the relationship between investor sentiment and volatility. These studies observed that noise traders who acted collectively on non-fundamental signals could introduce a systematic risk that is priced. In the De Long et al. (1990) model, price deviations from fundamental values resulting from changes in investor sentiment are uncertain. Arbitrageurs betting against mispricing run the risk in the short run, and tend to drive investor sentiment to a larger extreme, causing prices to deviate even further from fundamental values. The potential for loss and arbitrageurs' risk aversion reduces the size of the positions they are willing to take. This deters the arbitrageurs from completely eliminating mispricing, and, as a result, investor sentiment prevails as a significant factor that affects security prices in equilibrium. The De Long et al. (1991) model motivated Lee et al. (2002) to empirically test the proposition that conditional volatility and excess returns are affected by investor sentiment. They applied a simple framework with the assistance of GARCH in-mean models to determine how sentiment induces noise trading and affects trade-off between risk and return.

Verma and Verma (2007) extend the investigation by introducing a multivariate version of Nelson's EGARCH suggested by Koutmos and Booth (1995) on the asymmetric effects of bullish and bearish sentiments on stock volatilities. The two studies by Lee et al. (2002) and Verma and Verma (2007) show significant consistencies in findings, where they observed negative effects between investor sentiment and stock return volatility, and positive relationship between sentiment and stock market returns. Based on these findings, they conclude that sentiment is a priced risk factor that should always be taken into account when making investment decisions. Verma and Verma (2007) contend that there is an asymmetrical relationship where bullish sentiment has greater effects as compared to bullish sentiments on returns and conditional volatility. Meanwhile, Lee et al. (2002) finds that the magnitude of shifts in sentiment significantly impacts the conditional volatility of returns and expected returns. These findings thus validate the theory of the involvement of noise trader sentiment in influencing stock market volatility, underpinning the high-volatility behaviour of emerging markets.

2.6 Gaps in Literature

It is worth noting that an often-quoted explanatory factor for stock volatility is volatility of macroeconomic variables. For instance, Schwert (1989) analysed stock market volatility with macroeconomic volatility, and found that although the former was correlated with aggregate leverage, it only weakly predicted a small part of the volatility of stock movement. As an influential study on stock market volatility, Schwert's (1989) work was extended by Davis and Kutan (2003) by studying inflation and real output to stock's volatility in 13 developed and industrialised countries. Their results are consistent with Schwert (1989), i.e., that there is weak evidence of the predictive power of macroeconomic volatilities over stock market volatilities. In the context of Malaysia, the general failure to link macroeconomic fundamentals to stock return volatility also holds true in the case of asset pricing. With regard to volatility in the Malaysian equity market, Law (2006) and Angabini and Wasiuzzaman (2010) found higher volatility during the 1998 Asian financial crisis and 2008 global financial crisis on the Kuala Lumpur Composite Index. This scenario may be explained by over-reaction of investor sentiment during crisis periods of high uncertainty. This is further corroborated by Zakaria and Shamsuddin (2012), who found little evidence of the effect of macroeconomic variables on Malaysian stock market volatility. With these inconclusive findings, are macroeconomic variables alone sufficient to predict stock market volatility?

Evidence suggests that fundamental factors alone are not sufficient to explain the deviation of prices when the irrational behaviour of noise traders is proven to hold significant power over explaining returns. Nevertheless, conclusion about its predictive power in forecasting returns is still inconclusive, and theories have yet to unanimously concur upon in this field. Even definition and measurements are still debated among researchers. Measurement varies from surveys as direct proxies to numerous indirect proxies (closed-end fund discount, liquidity, volume, information on IPOs). However, with the introduction of innovative econometric techniques, more studies report significant relation between proxies representing sentiment to stock returns, either contemporaneously or long-term. On the contrary, emerging markets are scarcely researched with regards to this topic.

Previous empirical data dating back to the 1980s acknowledges the existence of non-fundamental factors that contribute to variation in stock prices. This has been at the heart of every debate in financial economics ever since Shiller's (1981) seminal paper. Since then, more papers suggested the significance of the irrational fad of investor sentiment that fuels price deviations. However, these studies have yet to verify the direct effect of investor sentiment proxies in explaining price deviation in Malaysian stock markets, which hold a different microstructure and unique stock market participant structure.

A growing body of research is concerned with the potential applications of behavioural finance in explaining stock price volatility and anomalies. Olsen (1998) writes that, based on empirical studies, investors who make decisions under stress tend to immerse in inevitable emotions which could result in greater price volatility. His study deems behavioural finance as a possible cause for stock price volatility. Despite suggestions that investor behaviour could instigate stock price volatility, other studies continue to disregard the behavioural aspect of finance, and continue to seek rational explanations behind it. Therefore, there is a gap that exists as an important determining factor of stock market volatility. Thus, one of the objectives of this thesis is to explore the effect of behavioural aspects (over and above the effect of fundamental factors) on explaining the volatility of the stock market. This is motivated by Shefrin and Statman’s (1994) suggestion that, without ignoring the importance of fundamental factors in an inefficient market, noise traders act as a crucial significant second driver of volatility. Therefore, the present study incorporates fundamental as well as non-fundamental determinants of Malaysian stock market volatility. This tests whether APT and BCAPT provide better predictive value incorporated in a model.

In an attempt to construct the composite investor sentiment index and its application to stock return volatility, the following chapter discusses the theories involved. It also addresses the development of the hypotheses in order to meet the research objectives in as stated in Chapter One. Figure 2.1 summarises the theories and empirical findings representing relevant articles that connect the efficient market theory and behavioural finance, as discussed in the present chapter.

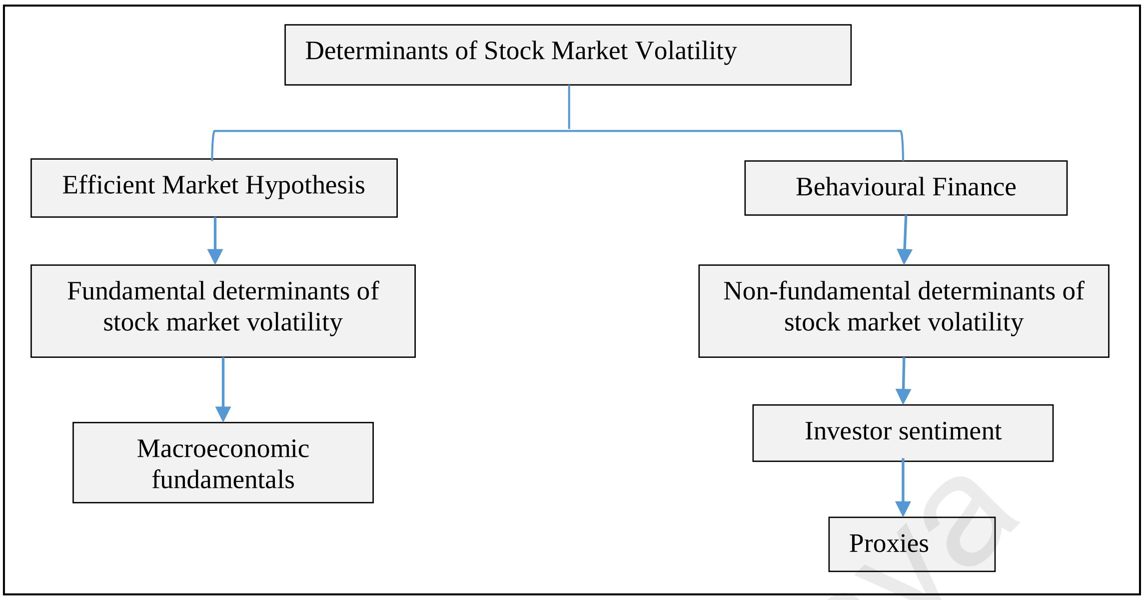


Figure 2.1 Summary of Literature Review

This chapter discussed two main theories in the framework of the study. Although they are contradictory paradigms, the efficient market hypothesis and behavioural finance paradigm may both be adopted in explaining the volatility of the stock market as advocated by BCAPT. APT and BCAPT provide solutions for risk-averse investors to allocate assets in a capital market within the framework of rational and irrational investor behaviour.

CHAPTER 3: RESEARCH FRAMEWORK AND HYPOTHESES

3.1 Introduction

Chapter Two highlights several gaps in literature that focus on the need to conduct comprehensive research on the volatility of the Malaysian stock market. To recapitulate, the areas identified as under-researched are: the effect of macroeconomic fundamental factors on stock market volatility, appropriate proxies to measure investor sentiment, and, the relationship between investor sentiment and stock market volatility. The purpose of this chapter is to present a framework for achieving the objectives of the study, in light of existing theories and previous empirical studies by researchers of traditional finance as well as researchers from the behavioural paradigm. The remainder of the chapter proceeds with a list of hypotheses related to the framework outlined.

Due to the inconclusive nature of existing empirical evidence regarding emerging stock markets, this thesis attempts to answer the following questions as stated in Chapter One:

1) Are macroeconomic fundamentals sufficient to predict the volatility of the Malaysian stock market?

2) Does investor sentiment predict the volatility of the Malaysian stock market?

3) Do macroeconomic fundamentals and the occurrence of a global financial crisis affect the predictability of investor sentiment on the volatility of the Malaysian stock market?

There methodological aim regarding research question 2 is to construct a relevant composite index for investor sentiment. Hence, measures to check the robustness of the constructed investor sentiment composite index are applied. Then the predictive power of investor sentiment on the volatility of stock market returns controlled by macroeconomic fundamentals and the 2008 global financial crisis are conducted. Further investigations are also carried out to identify the predictive value of macroeconomic fundamentals and investor sentiment on stock market volatility during the 2008 global financial crisis. The following section discusses the development of the research framework as illustrated in Figure 3.1.

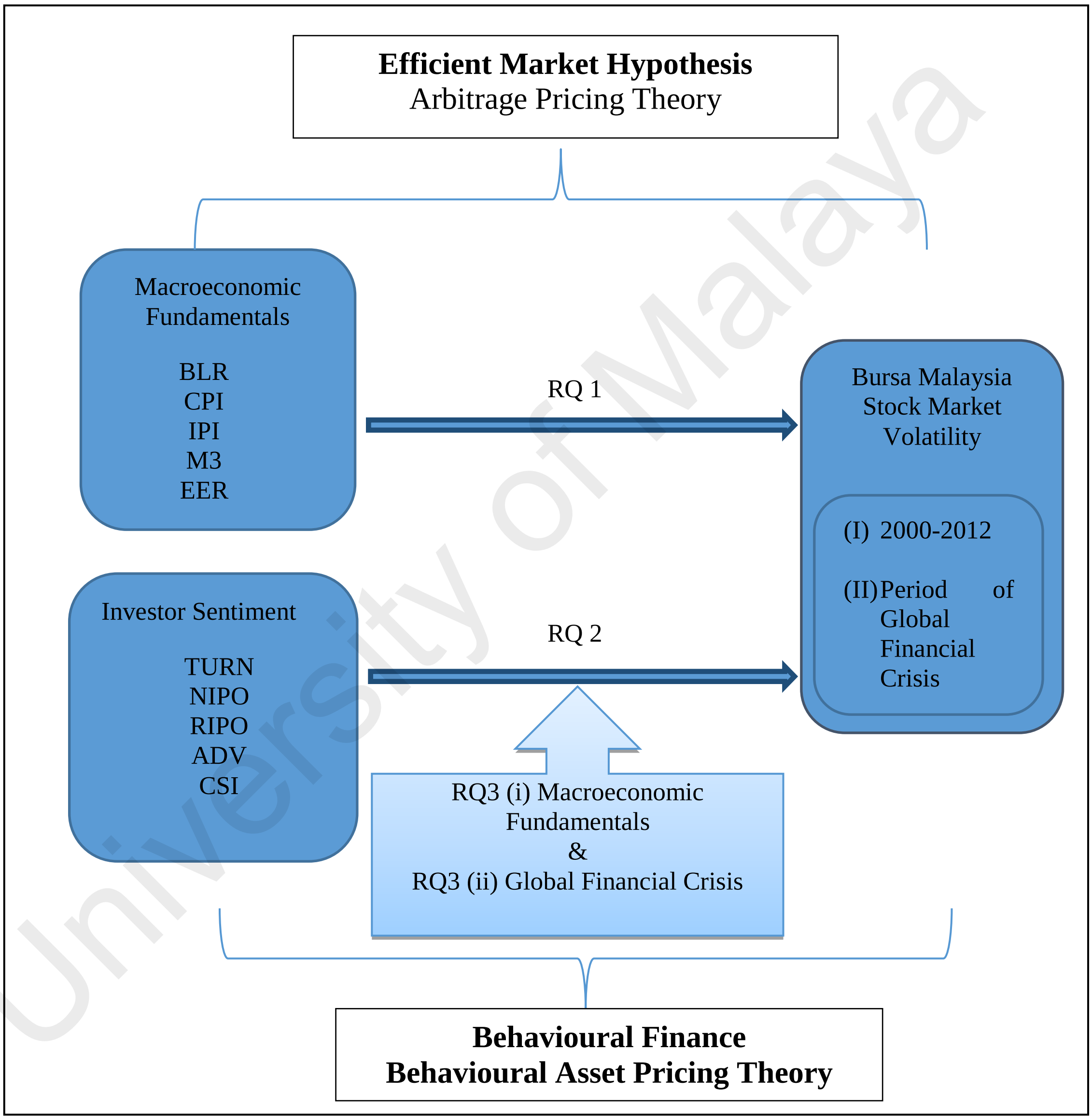


Figure 3.1 Research Framework and Theoretical Underpinnings

3.2 Relevant Existing Theories

This section discusses all relevant theories – including EMH – being the backbone of all theories of finance. The hypothesis is that prices act according to information available about the stock market, with the assumption that investors are rational and the market is efficient, and that no fundamental or technical analysis is able to predict future price movement of stocks. It is therefore impossible for investors to discover mispricing in order to beat the stock market. Many asset pricing theories have been developed based on the assumptions of an efficient market. This includes Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). CAPM holds that the only source of risk in an investment is its sensitivity to movements in the market portfolio. This is because any firm-specific risk can be diversified away by holding the market portfolio which contains all risky assets in the market. However, the concept of the market portfolio in CAPM is criticised, and a multifactor asset pricing model developed under the arbitrage pricing theory (APT) is viewed as an alternative to the CAPM in pricing assets in an efficient capital market. APT is employed to support the hypothesised relationship between macroeconomic fundamentals and stock market volatility in the context of an efficient market. The section resumes with the discussion of behavioural finance theory, which includes the theory of noise traders, and the hypothesised relationship between investor sentiment and stock market volatility – known as the Behavioural Capital Asset Pricing Theory. A dedicated subsection discusses the development of an investor sentiment index and the hypotheses delineated to test the relationships.

3.2.1 The Efficient Market Hypothesis

The efficient market is an important concept, widely accepted since its introduction in the late 1950s and early 1960s under the covenant of the "theory of random walk" in finance literature; the theory became known as the Efficient Market Hypothesis (EMH). In his empirical analysis of stock market prices that follow random walk, Fama (1965) defined an efficient market for the first time. Sewell (2011) summarised the extensive chronological review of notable literature relevant to the development of EMH.

EMH is an extension of the condition of zero-profit equilibrium certainty in classical asset pricing theory, to the dynamic behaviour of prices in speculative markets under conditions of uncertainty. In short, it expresses an efficient market if it is impossible to make economic profits by trading on the basis of information (Jensen, 1978). Given different types of information, EMH is described with three levels of market efficiency. Firstly, the *weak* form of EMH proclaims that all information on historical prices is fully reflected in the current market price of assets. This advocates that no analysis of the historical price patterns is useful to predict the future prices of shares. This is denoted by the term *random walk*, which means that the market price of shares is a random departure from previous prices. In other words, the future movement of prices is unrelated to historical price movements. Officially, the random walk model conditions that share returns are serially independent, and that the distribution of probability is constant over time. Sewell (2011) writes that the term random walk was coined in the letter *Pages of Nature* by Pearson in 1905. The subject of research that led him to conceptualise a simple random model was the optimal search procedure for finding a drunkard who had been abandoned in the middle of the park. It is an unbiased guess of the drunkard's future position since he will seemingly wander along in an unpredictable and random manner, and there may be a chance that the drunk will never come back to the starting point (Malkiel, 2003). The weak form of EMH has found broad-based recognition in the financial community, where technical analysis had previously not been held in high esteem. The stronger EMH claim that all widely available information is reflected in the current market price has proven to be more divisive among investment practitioners, who adopt fundamental analysis as a widely acknowledged method of analysis.

The next form of efficiency is semi-strong, which incorporates the weak form hypothesis. In general, all publicly available information and past information is so swiftly integrated into current prices that fundamental and technical analyses are less likely to be successful. The strong form of EMH notes that if the market is strong form efficient, it reflects both public as well as private information, integrating the weak and semi-strong form EMH. According to strong form EMH, all information – for instance, stock splits, dividend and merger announcements – is well incorporated into the current market value of shares. In this respect, technical analysis and fundamental analysis cannot be used to beat the market to earn abnormal returns.

3.2.2 Arbitrage Pricing Theory

Existing capital market theories provide the foundation for the development of financial asset pricing models in an efficient market. This view of mainstream capital markets is based on the assumption of a perfect-world scenario where markets are informationally efficient and asset prices adjust quickly and accurately, reflecting new information in the market. Additionally, all investors are considered risk-averse and rational in making their decisions. As discussed in Chapter Two, asset pricing theory asserts that stock market volatility is closely related to the movement of macroeconomic variables (Schwert, 1989) as a result of fundamental economic information reflected in the stock market. This supports the APT developed by Ross (1976), which asserts that asset pricing is influenced by the price risk factor of macroeconomic fundamentals. In order to investigate and support the existence of macroeconomic fundamentals in predicting stock volatility, particularly in the Malaysian stock market, the first hypothesis in this study tests this relationship. The theory forms the basis of the first research objective of this study, which is to examine the effect of macroeconomic fundamentals on the volatility of the Malaysian stock market. Specifically, it is postulated that the variables in macroeconomic fundamentals cause the volatility of the Malaysian stock market with the assumption of an efficient market. This is reflected in the first research hypothesis:

Hypothesis 1: Macroeconomic fundamentals significantly predict Malaysian stock market volatility.

3.2.3 Behavioural Capital Asset Pricing Theory (BCAPT)

The BCAP proclaims that in an inefficient market, noise traders act as a second driver, committing cognitive errors and steering prices away from efficiency (Shefrin and Statman, 1994). In BCAPT, the expected returns of securities are determined by their behavioural betas, which are relative to the tangent mean-variance efficient portfolio, not the market portfolio, as depicted in Figure 3.2.

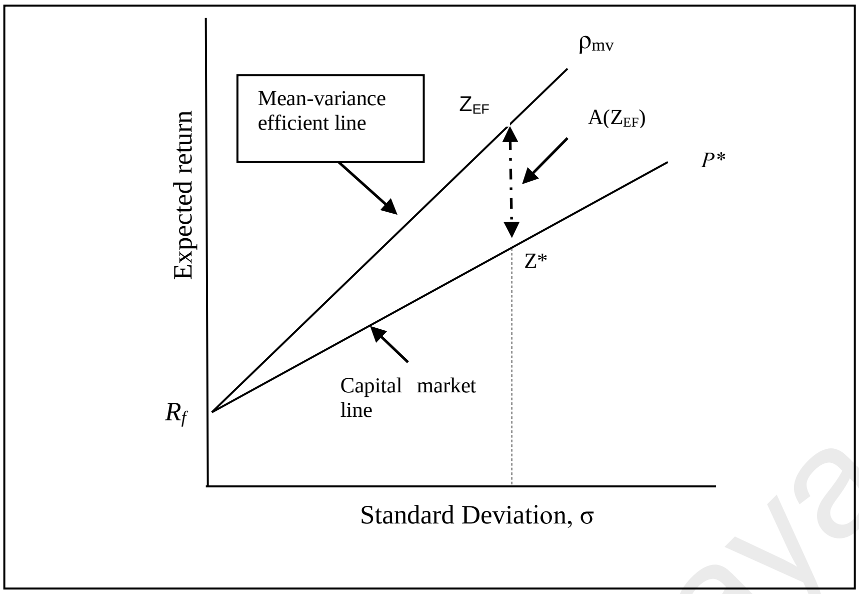


Figure 3.2 Mean-Variance and Capital Market Line Deviation

In Figure 3.2, mean-variance efficient risk-return line from risk-free rate through the risk-free return point for ρ_{mv} is depicted, and market factor *P** is depicted by the capital market line from risk-free rate through the risk-return point. This theory contradicts the assumption of an efficient market as proposed by EMH that is applied in constructing Hypothesis 1.

In summary, the theory is derived based on the existence of price efficiency in the presence of noise traders through a comprehensive framework. The framework depicts what happens when the market is inefficient and noise traders act as crucial second drivers. In such a situation, new information is no longer a sufficient marker. Hence, old information continues to affect prices and volatility, and manifests in increased trading volume. This theory is grounded insofar as it tests the effect of fundamental and non-fundamental factors to the movement of stock prices in the final part of the analysis chapter. The following section analyses the psychological factors that indicate the possible existence of investor sentiment. The theory discusses the role of noise traders in the movement of stock returns and volatility.

3.2.4 The Theory of Noise Traders

Apart from the effect of optimistic and overconfident investors, trading on noise plays a crucial role in stock market volatility. Noise traders form erroneous beliefs about the future distribution of returns on risky assets. Beliefs from pseudo-signals are treated as if they are information. The reasons for such behaviour are unclear, as they could be attributed to one or more of the psychological biases in processing information and forecasting returns. Alternatively, investors may incorrectly underestimate the risk of returns, perhaps because they are optimistic. Arbitrage is defined as the simultaneous sale and purchase of the same or essentially similar securities from two different markets, in order to take advantage of price differences. Arbitrageurs play a vital role in the analysis of securities markets – in bringing the prices of assets close to their fundamental values and keeping the market efficient – which is the fundamental concept of the Efficient Market Hypothesis. In an imperfect stock market, there are two types of agents: arbitrageurs and noise traders. This alternative approach to efficient markets, however, rests on two assumptions as discussed below.

First, investors are not fully rational, and their demand for risky assets is affected by their beliefs or sentiments which are not fully justified by fundamental news. Second, arbitrage is risky and therefore limited. Arbitrageurs have a short horizon where there are perfect substitutes. However, securities that are perfect substitutes still pose a limit to arbitrage even with an infinite horizon of arbitraging,. This assumption is justified in many ways. Most arbitrageurs are agents for investors who regularly evaluate the performance of investment in relatively short intervals. Therefore, corrections of mispricing that take longer periods than horizon monitoring lose to the expectations of investors, and hence reduce arbitrageurs' pay. Moreover, arbitrageurs face the risk of liquidation of assets if prices move against them, and the value of collateral falls. This risk nonetheless reduces the arbitrageurs' tolerance towards noise trader risk. The imperfect market is subject to shifts of investor demand that are not completely rational. These demand changes are likely to be a response to changes in anticipation or sentiments that are not fully explained by fundamentals. Such changes may be in response to pseudo-indications that investors consider as reliable information, but do not convey as much information as they would in an entirely rational model (Black, 1986). Moreover, with correlated trading strategies and popular asset pricing models, investors tend to create aggregate demand shifts and are therefore unable to cancel out each other's trade, as would be the case in an efficient market.

The argument that noise traders lose money and ultimately vanish continues to be undeniable as of yet. With overconfidence and high optimism on private information, noise traders tend to bear more risk than arbitrageurs as a result of their aggressiveness. Noise traders potentially earn higher expected returns despite buying high and selling low on average, if risk-taking is compensated in the market. Although the reward does not need to be fundamental – it can also be in the form of resale price risk originating from the unexpected future opinions of noise traders. Expecting higher returns, noise traders as a cluster do not entirely disappear from the market as presumed by the EMH. In this kind of market, prices fluctuate more than what is justified by fundamentals, resulting from responses to shift in sentiments and news (Shiller, 1981; 1984). The effect of demand shifts on prices is larger when most investors trail the textbook models of finance and inactively hold the market portfolio. In this case, a shift in the sentiment of some investors is refuted by a change of position among only a few arbitrageurs and not all market participants. The effect of a sentiment shift on price is determined by the size of the risk bearing capacity of arbitrageurs. Furthermore, this systematic effect of sentiment has a price in equilibrium. Therefore, assets that are affected by the caprice of investor sentiment are expected to yield higher average returns than similar assets that are not affected by such caprice.

3.2.5 Relative Returns of Noise Traders and Arbitrageurs

Noise trader sentiment increases the risk of returns to assets. Hence, if noise traders' portfolios are concentrated in assets that are subject to noise trader risks, noise traders can earn higher average rate of return on their portfolios compared to arbitrageurs. The conditions are explained by equation 3 below, wherein all agents earn a net return of *r* on investments in asset *s*. The difference in their holdings in the risky asset *u* multiplied by the excess return paid by a unit of that asset makes up for the difference between noise traders' and arbitrageurs' total returns, given equal initial wealth. This difference in returns to the two types of agents is denoted as:

$$\Delta R_{n-a} = (\lambda_t^n - \lambda_t^a)[r + p_{t+1} - p_t\,(1+r)] \tag{3}$$

Some calculations show that the expected value of this difference is given by

$$E(\Delta R_{n-a}) = \rho^* - \frac{(1+r)^2(\rho^*)^2 + (1+r)^2\sigma_\rho^2}{(2\gamma)\mu\sigma_\rho^2} \tag{4}$$

The equation above requires that the mean perception ρ^* of returns on risky assets must be positive in order for noise traders to earn higher expected returns. The first ρ^* on the right hand side of the equation increases noise traders' expected returns through what is called the "hold more effect". When noise traders on average hold more of the risky asset, and earn a larger share of the reward of risk bearing, the noise traders' expected returns relative to an increase in arbitrageurs. When ρ^* is negative, noise traders' changing misunderstandings still make the fundamentally riskless asset *u* risky, and still enhance the expected return on asset *u*, but the rewards to risk bearing inexplicably accumulate for arbitrageurs, who on average hold more of the risky asset than noise traders do. Interestingly, a positive ρ^* corresponds to excessive noise trader optimism, which Kahneman and Riepe (1998) describe as a common bias in judgement. Therefore, overconfident noise traders drive investments in risky and unsafe assets *u* by overinvesting in them. The "price pressure effect" is incorporated by the first term in the numerator.

As noise traders grow more bullish, they claim more of the risky assets on average, which results in asset price increase. This reduces the return to risk bearing, hence also reducing the differential of returns between noise traders and arbitrageurs. The "Friedman effect", which entails a "buy high sell low" effect, is incorporated as the second term in the numerator of the equation. Noise traders seem to exhibit bad market timing due to their stochastic misperceptions. The heart of the model of the denominator incorporates the "create space effect". The price risk increases in tandem with the variability of the noise traders' beliefs, and in order for arbitrageurs to take advantage of the misperception, they are required to bear the excess risk. Since arbitrageurs are risk-averse investors, they reduce the extent to which they bet against noise traders in response to this increased risk. The "price pressure" and Friedman effects inflict less damage on noise traders' average returns relative to arbitrageurs' returns if the "create space" effect is large. The "hold more" and "create space" effects tend to raise noise traders' relative expected returns, while lower noise traders' relative expected future returns are affected by the Friedman and "price pressure" effects.

However, neither pair evidently controls the returns. Noise traders do not earn higher average returns if they are on average bearish, because if p^* does not exceed zero, there is no "hold more" effect, and the equation must be negative. Nor can noise traders earn higher average returns if they are above average bullish; as p^* increases, the "price pressure" effect increase $(p^*)^2$ dominates. However, noise traders potentially earn higher expected returns if the degree of average bullishness is intermediate in range. BCAPT and Noise Trader Theory act as the grounded theories of this study with regards to the association of non-fundamental variables to the movement of stock prices. The weakness of traditional theories in predicting stock market volatility leads this study to include investor sentiment as a significant factor in influencing volatility, which motivates the testing of the second hypothesis:

Hypothesis 2: Investor sentiment significantly predicts Malaysian stock market volatility.

This hypothesis will test two specific periods: (i) the whole period of study (2000 to 2012), and (ii) the sub-period of the global financial crisis. Development of hypothesis 2 (i) is driven by the findings and observations of Angabini and Wasiuzzaman (2010) and Law (2006) in regard to the extreme volatility found during periods of crisis in the case of the Malaysian stock market. This is expected to answer research question 2 in verifying the role of investor sentiment in the fluctuation of the Malaysian stock market. In order to test the abovementioned relationships, it is crucial to determine an appropriate measure of investor sentiment in the Malaysian stock market. Upon testing the proxies and constructing the investor sentiment composite index, the second hypothesis tests the effect of the investor sentiment composite index on stock market volatility.

3.3 Construction of Investor Sentiment Index: Supporting Theories

This section describes the proxies that will be included in the investor sentiment composite index. As discussed in Chapter Two, each of the proxies adopts the closest possible measurement to represent investor sentiment in most developed stock markets. These proxies are justified by previous empirical studies, and a brief discussion will also be presented on the optimism and overconfidence behaviour of investors.

3.3.1 Optimism and Overconfidence

The essence of the sentiment function in this study is affected by at least two behavioural phenomena in making investment judgements which normally lead to underestimation of future volatility: optimism and overconfidence. Decision theorists argue that since the outcomes of possible options are unknown in advance, any significant decision can be described as a choice between gambles (Raiffa, 1968). People assign value to outcomes with the added combination of their beliefs in forming preferences about risky options. However, this judgement can be systematically done with errors. This is known as judgement bias. Investors who are prone to these biases tend to take risks that they do not acknowledge, experience outcomes they do not anticipate, and are exposed to unjustified trading. The current framework takes into consideration investor sentiments induced by the judgement errors of being overly optimistic and overconfident.

Optimism is a powerful bias that has asymmetrical effects. Optimists exaggerate their judgement, underestimate the likelihood of bad outcomes over which they do not have any control, and are also prone to illusions of control (for instance, they exaggerate the degree to which they control their fate). When proponents of behavioural finance speak of “sentiment”, they are referring to the aggregate errors of investors that manifest in stock prices. In common cases of irrational exuberance and stock prices, investor sentiment is regarded as excessive optimism, resulting in erroneous judgement in investment decisions.

Another powerful psychological bias affecting investors’ judgement is overconfidence. By definition, it is the tendency to place an irrationally excessive degree of confidence in one’s abilities and beliefs (Grinblatt and Keloharju, 2009). This bias leads the investor to form judgements with excessive weight on private signals, and places less validity on the market’s valuation (Daniel, Hirshleifer, and Subrahmanyam, 1998). This generates a larger willingness to trade than would be observed in less confident investors. The combination of these two judgemental biases is a robust synthesis, which causes investors to overestimate their private information, underestimate risks, and exaggerate their ability to control events (Kahneman and Riepe, 1998). A study by Odean (1998) comprehensively examined investors who were overconfident, defined as above average traders, to volume and volatility. It is worth noting that as one of the judgement biases, overconfidence is costly to society, mostly a result of spending too many resources on information acquisition and overtrading. Hence, overconfidence increases trading volume subsequent to market gains, as shown by Figure 3.3 (Gervais and Odean, 2001; Statman, Thorley, and Vorkink, 2006).

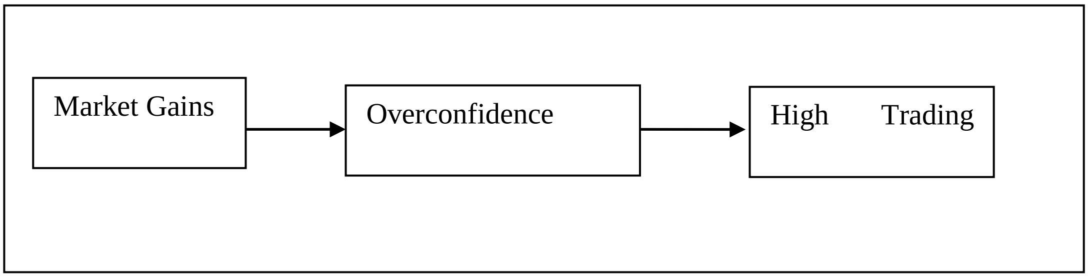


Figure 3. 3 The Relationship between Market Gains, Overconfidence, and High Trading (Source: Gervais and Odean, 2001)

Theoretically, the overconfidence bias leads investors to be too certain of their views, which results in their underestimation of risk, contributing to excess liquidity. In other words, irrational investors believe that a liquid market will indefinitely continue to make more trades, leading to enormous credit expansion. This was the root cause of the 2008 financial crisis (Shefrin, 2009). Several studies (for instance, Daniel et al., 1998) also suggest that overconfidence constitutes an important reason for excessive price volatility, Daniel et al. (1998) demonstrates that overconfident investors increase price volatility to the reaction of private signals. These factors manifest as increased investor demand on tradable stocks; this warrants the inclusion of proxies to measure investor sentiment on the investor sentiment composite index. In order to test the second hypothesis, it is crucial to determine appropriate proxies that measure the sentiment of Malaysian stock market investors. Therefore, the hypotheses positing the significance of proxies to the investor sentiment index and the development of the investor sentiment composite index will be tested next.

The idea of including stock market turnover as one of the proxies on the sentiment index stems from Baker and Stein's (2004) method of measuring liquidity. The researchers suggest that liquidity could serve as a sentiment index. This is illustrated in a market with short sales constraints, where high optimism irrational investors participate to add liquidity, and therefore lead to the symptoms of market over-valuation. The authors briefly discuss the correlation of stock market turnover with direct surveys available in the U.S. However, information about the nexus between market turnover and stock market volatility is scarce. It is thus crucial to test the effect of liquidity proxies on the volatility of the Malaysian stock market in order to observe any new evidence of this. The hypotheses are:

H2a: Stock market turnover significantly predicts Malaysian stock market volatility.

The number of IPOs and first day returns of IPOs are also signs of overconfidence and optimism among investors. The IPO market is often viewed as a sensitivity indicator of investor sentiment. The underlying demand for IPOs is often sensitive to sentiment, with investment bankers referring to it as “windows of opportunity”. Such impulses could explain wild fluctuations in IPO volume, with high rate of listings in some months and none in others (Lowry, 2003). High first day returns indicate investors’ optimism towards stock market conditions. In addition, low idiosyncratic returns of IPOs are often interpreted as symptoms of market timing (Stigler, 1964; Ritter, 1991). The number of IPOs as well as their initial return are expected to significantly predict Malaysian stock market volatility.

H2b: Number of IPOs significantly predicts Malaysian stock market volatility.

H2c: Initial IPO returns significantly predict Malaysian stock market volatility.

The next proxy is advance/decline ratio, which may variably be interpreted as bullish or bearish sentiment, depending on momentum or contrarian strategies undertaken by investors (Brown and Cliff, 2004). The ratio is adopted globally by most technical analysts as a sign of investor confidence in the market, along with other indicators (Neal and Wheatley, 1998). The following hypothesis seeks to test the relationship between advance decline ratios and Malaysian stock market volatility, in order to confirm this ratio as one of the closest measures to represent investor sentiment.

H2d: Advance/decline ratio significantly predicts Malaysian stock market volatility.

The Consumer Sentiment Index (CSI) is the final proxy that may also be the closest measure of investor sentiment. Although it was initially accepted as a measure of household sentiment in the general economy, studies have increasingly found encouraging results with regard to its use in the equity market. CSI, being available in most countries, has recently gained popularity in representing investor sentiment. This thesis examines its connection with Malaysian stock market volatility, testing whether it fulfils the criteria to be taken into account as a proxy for investor sentiment. Hence the hypothesis is:

H2e: Consumer sentiment index significantly predicts Malaysian stock market volatility.

The detail of how these proxies are incorporated into the investor sentiment composite index is described in Chapter Four. Once the measurement of investor sentiment has been delineated, it is crucial to observe what effect it has on the dependent variable, stock market volatility. The results will offer insight into the behavioural finance paradigm, confirming the contribution of non-fundamentals to the movement of asset pricing. The nexus between non-fundamental factors and stock market volatility has mainly been attributed to the Theory of Noise Traders, which will be described next. The theory motivates the testing of further hypotheses relating to the development of the investor sentiment composite index and the relationship between investor sentiment and stock market volatility. Figure 3.4 illustrates the relationship between each proxy on the investor sentiment composite index and the dependent variable. These steps are taken in order to observe the robustness of each proxy in the construction of the composite index.

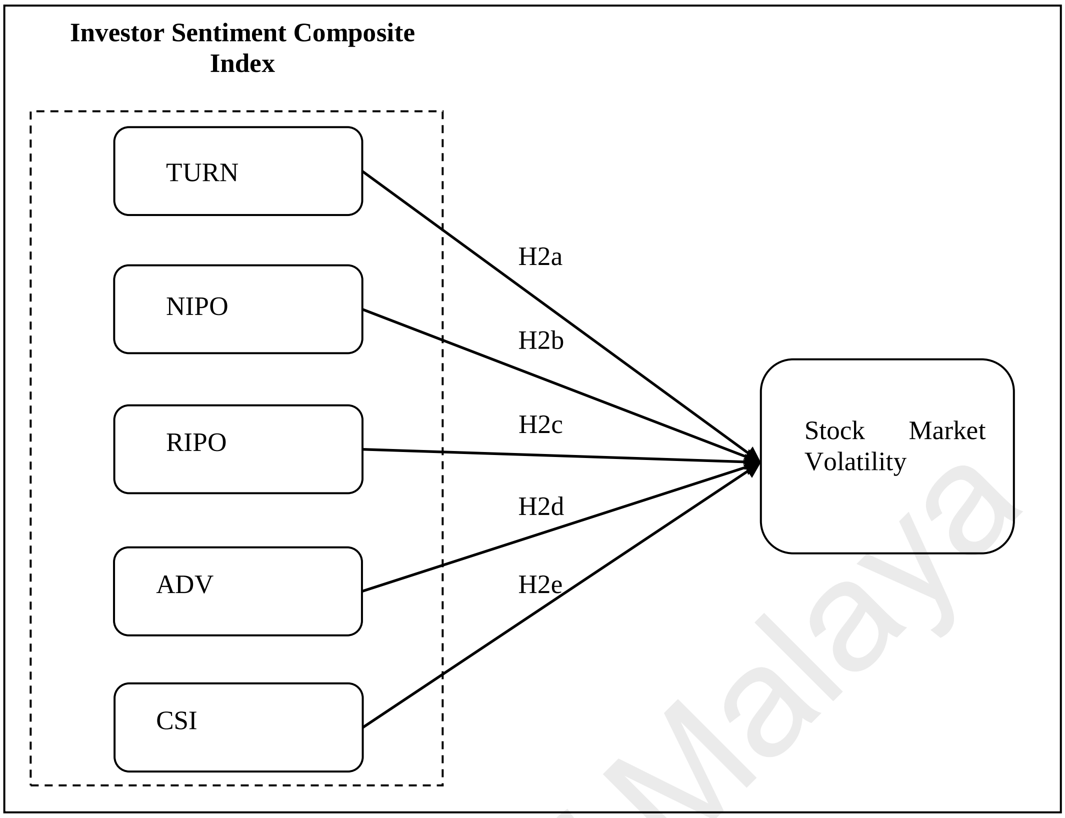


Figure 3.4 Construction of the Investor Sentiment Composite Index

The general purpose of this thesis is to identify the determinants of stock market volatility – whether it is caused by fundamental or non-fundamental factors, or both. Numerous studies report different observations on the relationship between these factors and stock market volatilities. In order to meet the research objective, this thesis is grounded in the Behavioural Capital Asset Pricing Theory (BCAP). This thesis integrates multiple independent variables from fundamental and non-fundamentals factors into a single framework, as illustrated in Figure 3.3. Note that the relationships between the dependent and independent variables are controlled by macroeconomic variables and the global financial crisis of 2008.

For robustness check, Hypothesis 3 tests the predictability of macroeconomic factors on investor sentiment. This test determines whether investor sentiment maintains its significance in predicting stock market volatility for the duration of the study.

Hypothesis 3 (i): Macroeconomic fundamentals have no effect on the predictive value of investor sentiment on the volatility of the Malaysian stock market.

Hypothesis 3 (ii): The occurrence of a global financial crisis has no effect on the predictive value of investor sentiment on the volatility of the Malaysian stock market.

An extension of the thesis that is worth researching is the behaviour of the relationships between macroeconomic fundamentals and non-fundamental factors and the volatility of the stock market during periods of financial crisis. This aligns with the findings of studies that observe abnormal volatility during periods of crises (Bartram and Bodnar, 2009; Horvath and Poldauf, 2012).

3.4 Summary

The main objective of this thesis is to research the determinants of stock market volatility in the Malaysian context. Starting with the efficient market hypothesis, the Arbitrage Pricing Theory holds that any fluctuations in stock market returns are contributed by the movement of macroeconomic fundamentals. However, the Behavioural Capital Asset Pricing Theory suggests that the effect of investor sentiment may surpass the effect of macroeconomic fundamentals on stock market volatility. BCAPT also justifies the incorporation of two different paradigms in this thesis, namely, the efficient market theory, and theories of behavioural finance, emphasising the importance of investor sentiment as a second driver of stock market volatility.

In testing the noise trader theory of inefficient markets, this thesis uses the widely accepted definition of investor sentiment, leading to the construction of a composite index comprising all five proxies as discussed in existing literature. Finally, the main hypotheses were reviewed, although these will be discussed in greater detail in the subsequent chapter. Chapter Four discusses the research methodology employed in this study. Table 3.1 summarises the hypotheses discussed in this chapter.

Table 3.1 List of Research Hypotheses

Hypothesis	**Statement**
Hypothesis 1 (i)	Macroeconomic fundamentals significantly predict Malaysian stock market volatility during the period of study (2000-2012).
Hypothesis 1 (ii)	Macroeconomic fundamentals significantly predict Malaysian stock market volatility during the sub-period of the global financial crisis.
Hypothesis 2 (i)	Investor sentiment significantly predicts Malaysian stock market volatility during the period of study (2000-2012).
Hypothesis 2 (ii)	Investor sentiment significantly predicts Malaysian stock market volatility during the sub-period of the global financial crisis.
Hypothesis 3 (i)	Macroeconomic fundamentals have no effect on the predictive value of investor sentiment on the volatility of the Malaysian stock market.
Hypothesis 3 (ii)	The occurrence of a global financial crisis has no effect on the predictive value of investor sentiment on the volatility of the Malaysian stock market.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

This chapter discusses data sources and research methodology that will be applied to answer the research questions. In doing so, the chapter begins with a recapitulation of the research questions stated in Chapter One. The research questions are:

1) Are macroeconomic fundamentals sufficient to predict the volatility of the Malaysian stock market?
2) Does investor sentiment predict the volatility of the Malaya stock market?
3) Do macroeconomic fundamentals and the occurrence of a global financial crisis affect the predictability of investor sentiment on the volatility of the Malaysian stock market?

Although the topic of this thesis is partly adopted within the behavioural finance paradigm, it does not intend to perform an in-depth study of the psychology of investor behaviour. This thesis aims to identify investor behaviour through proxies recommended by relevant empirical studies. Thus, the positivist school of thought is adopted, which believes that the phenomenon of sentiment is external, and has a demanding and independent stance in its observation of the variables. The research questions involve real-world issues which normally rely on econometric techniques for empirical evidence. This approach stems from the classical science paradigm (Dorfman and Tippins, 2006). Therefore, quantitative research and the statistical method are embraced in order to remain independent and objective regarding the research topic.

One of the advantages of quantitative studies is that the results are reliable when an accurate representation of the population is studied. Therefore, research findings can be generalised when data are based on randomised samples of sufficient size. Additionally, it enables the researcher to test and validate the constructed theories. Research results from quantitative studies are researcher independent, therefore, free of biased. A quantitative approach also gives the researcher the ability to test hypotheses that are constructed before data collection, and studies are thus replicable on other segments of the population. The obvious option is therefore to employ econometric analysis on secondary data, which has its own advantages. Apart from data readily accessible online from sources such as Bursa Malaysia, the Department of Statistics, and Bank Negara Malaysia, secondary data are also gathered from third-party data providers such as Bloomberg, Inc. This effectively eliminates the need to carry out primary research at one's own cost. The next section details the nature of the data that will be collected for analysis.

4.2 Data

The data are extracted from published information provided by primary and secondary data providers. They comprise of the returns of KLCI, information on five macroeconomic variables, and information on five indirect proxies for the construction of investor sentiment composite index. All variables are extracted in monthly frequency, in order to promote consistency throughout the sample period that spans from the beginning of the new millennium until 2012.

4.2.1 Dependent Variable: The Volatility of Kuala Lumpur Composite Index (VKLCI) Stock Returns

The KLCI is adopted to represent Bursa Malaysia's stock market performance. It is the main index that captures the interests of investors worldwide, representing the health of stock prices. The data employed here are extracted from the major Malaysian stock market indicator – the Kuala Lumpur Composite Index (KLCI) – which comprises top 100 stocks in terms of market value capitalisation in Malaysia. The index is selected to represent stock market indicators well known to investors, measuring the health of the local stock market as well as the performance of investment portfolios. In this respect, KLCI may also determine the direction of investor sentiment towards current and future performance of the Malaysian stock market.

Data are in monthly series, averaged from daily frequencies spanning January 2000-December 2012. Data from the period of the globally-affected sub-prime crisis of the U.S. of 2007-2008 are also included. The sources of data are provided by Bloomberg Inc. as well as the website of the Malaysian stock exchange (Bursa Malaysia). KLCI returns are computed from the monthly fluctuations of KLCI prices following equation (5):

$$R_i = Ln\left(\frac{P_t}{P_{t-1}}\right) \tag{5}$$

where P_t is the price of *KLCI* on day *t*, P_{t-1} is the offer price at *t-1*.

In line with the objective of this thesis, the volatility of KLCI is modelled using the best possible tools. In fulfilling the robustness of measurement, volatility is measured using one of two popular methods: the French et al. (1987) measure of volatility and the ARCH family measure of volatility. Following French et al. (1987), volatility is estimated as the square root of sum of squared daily returns, plus twice the sum of adjacent returns. The formula is as follows:

$$o_{m,t2} = \sqrt{\sum_{i=1}^{Nt} r_{i,t2}^{2} + 2\sum_{i=1} r_{i,t} r_{i,t+1}} \tag{6}$$

where N_t is the daily returns of $r_{i,t}$ during the month t and $r_{i,t+1}$ is the returns during the month *t+1*. This estimator has three advantages over the rolling 12-month standard deviation method introduced by Officer (1973) and Merton (1980). The first advantage is that the accuracy of the standard deviation estimate is increased by sampling the return process more frequently. Secondly, a more precise estimation is obtained by using returns of a particular month. Finally, this estimation uses a non-overlapping sample of returns, highlighting variation in estimated volatility.

Another way to model volatility is using measures from the family of ARCH effects. This technique requires checking the presence of ARCH effects. As a simple measure in the Breusch-Pagan test, it involves testing the null hypothesis that the variances are homoscedastic, $\gamma_0 = \gamma_1 = \gamma_2 = ... = \gamma_q$. The resulting test statistics follows a χ^2 distribution with q degrees of freedom, and if the result is highly significant, the hypothesis is rejected, suggesting evidence of an ARCH (1) process. Engle (1982) provides details of the autoregressive heteroscedasticity order by specific tests of the ARCH process. Engle's idea starts with the fact that the variance of residuals (σ^2) should be allowed to depend on history, and to contain heteroscedasticity. In fact, conditional variance does not necessarily depend on a single lagged realisation, but on more than one. For example, an ARCH (1) process is:

$$Y_t = \alpha + \beta X_t + u_t \tag{7}$$

where $u_t | \Omega_t \sim iid, N(0, h_t)$, and

$$\sigma_t^2 = \gamma_0 + \gamma_1 \sigma_{t-1}^2 \tag{8}$$

The ARCH (1) model shows that when a big shock occurs at period *t-1*, it is more likely that the value of u_t will be bigger. Nevertheless, the conditional variable may depend on more than a single lagged realisation for each case, producing a different ARCH process. In general, an ARCH (q) process is given by:

$$\begin{aligned} \sigma^2 &= \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_1 u_{t-2}^2 + \ldots + \gamma_q u_{t-q}^2 \\ &= \gamma_0 + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \end{aligned} \tag{9}$$

The next step is to observe whether there is a higher order ARCH effect; therefore, a Breusch-Pagan test is re-conducted with an order of 2 and 3 as the *q*-term. If the ARCH effect disappears at the higher order, q>2, KLCI returns may suffer from the presence of autoregressive heteroscedasticity up to ARCH (2). Since it is common to measure conditional volatility of stock returns in the Malaysian stock market with GARCH (1,1) as evidenced from previous studies[3], there is a possibility that KLCI suffers from a similar effect. Therefore the modelling of the GARCH effect, which takes into account the lagged conditional variance terms following Bollerslev (1986), will be included. The general form of GARCH (p,q) takes the following form:

$$\begin{aligned} &Y_t = \alpha + \beta X_t + u_t \\ &\text{where } \mathrm{u_t} \,|\Omega_\mathrm{t} \sim iid \ \mathrm{N}(0, h_t) \end{aligned} \tag{10}$$

$$h_t = \gamma_0 + \sum_{j=1}^{q} \delta_i h_{t-1} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \tag{11}$$

[3] Angabini and Wasiuzzaman (2010), Law (2006), Lim (2008), Angabini and Wasiuzzaman (2011); Albaity and Shanmugan (2012), and Zakaria and Shamsuddin (2012)

4.2.2 Independent Variables: Macroeconomic Fundamentals

Achieving the first objective of this study requires information regarding macroeconomic conditions in Malaysia. Macroeconomic variables consist of: the base lending rate to represent interest rate, consumer price index to represent inflation rate, and effective exchange rate provided by the Bank for International Settlements (BIS) to represent the exchange rate. Finally, the industrial production index and the broad money supply represent real output and money in circulation. Each variable is discussed in the next section.

Base Lending Rate (BLR)

Base lending rate is applied in many countries as a reference for interest rate offered by commercial banks to borrowers. It is the minimum interest rate calculated by banking institutions based on a formula which takes into account the institutional cost of funds and other administrative charges. It undergoes constant adjustments depending on the state of the economy. Generally, BLR rises when the money market is on the uptrend and vice versa. Changes in the rate have a direct relationship with credit available to customers (Scholnick, 1996). In a nutshell, when people are refrained from extensive borrowing due to high BLR, they are induced to save in anticipation of future consumption needs that cannot be financed through credit. This partly affects the circulation of money in the economy, and impacts liquidity in the local stock market.

The Consumer Price Index (CPI)

The CPI, based on Laspeyres formula, is an often-quoted index for the computation of inflation; it measures the average rate of change in prices charged by domestic producers of commodities or products originating from a number of industrial sectors, namely, agriculture, forestry, logging and fishing, mining and quarries, manufacturing and water, gas and electricity. Monthly data on CPE are available from Bank Negara Malaysia.

Effective Exchange Rate (EER)

EER is adopted to replace the exchange rate between the Malaysian ringgit (MYR) and the United States dollar (USD). This is because the rate was pegged at MYR3.80 per USD by the Government of Malaysia during the 1998 Asian financial crisis. Available on a monthly basis, EER is computed from the geometric weighted averages of bilateral exchange rates from a basket of 67 currencies in the world. It serves the function of measuring international competitiveness and components of monetary/financial condition indices. It also gauges the transmission of external shocks, and becomes an intermediate or operational target for monetary policy. Therefore, EER is essential for policymakers as well as market participants, and is the closest candidate to represent the exchange rate (Klau and Fung, 2006).

Industrial Production Index (IPI)

The industrial production index represents the real output of a country. It is released in monthly frequency by the Department of Statistics Malaysia, which measures the amount of output from the manufacturing, mining, electric, and gas industries. Industrial production and export performance are primarily high-frequency variables for measuring economic growth of a country. This variable may have a significant effect on stock market volatility as reported by previous empirical studies (Engle, Ghysels, and Sohn, 2013). It is relevant as one of the independent variable in this thesis.

Broad Money Supply in the Economy (M3)

Broad money supply in the economy is represented by money aggregate (M3). It is widely used by economists to estimate the amount of money in circulation. Being the broadest measure of an economy's money supply, it tends to impose major impact on the economic condition and performance of the local stock market. Available in monthly frequency, this variable is selected in light of widely-cited studies on macroeconomic fundamentals in Malaysia (Ibrahim and Aziz, 2003; Rahman, Sidek, and Tafri, 2009; Shaharudin and Hon, 2009). Thus, the effect is relevant to the dependant variable of this study.

4.2.3 Independent Variables: Proxies for Investor Sentiment

Market Turnover (TURN)

Most liquidity proxies are normally measured by daily trading volume and prices. In order to increase accuracy, daily security prices are scanned for missing data, errors, and delisting, and later averaged to obtain monthly series. The measurement for liquidity is stock market turnover (TURN) as adopted from Baker and Stein (2004).

$$TURN = \frac{\textit{monthly trading volume}}{\textit{average shares listed}} \qquad (12)$$

Cumulative Advancing and Declining Stocks (ADV)

Data are initially in daily frequency, and then averaged to monthly data in order to constitute the advancer-to-decliner ratio in monthly samples. The data are truncated at zero, as the numerator and denominator of these variables have the tendency to move in opposite direction (Brown and Cliff, 2004).

$$ADV_t = \frac{\textit{number of advancing stocks}}{\textit{number of declining stocks}} \qquad (13)$$

The Number of Initial Public Offerings (NIPO)

NIPO refers to the number of monthly initial public offerings, and offer price and closing price on the first day of all IPOs during the sample period. The number of Initial Public Offerings (NIPO) is the log of the total number of IPOs for a particular month.

NIPO = number of IPOs of firms that go public during the month (14)

The Initial Returns of Initial Public Offerings (RIPO)

RIPO represents the average initial first day return on a given month's offerings. The calculation is as described in the IPO under-pricing anomalies' empirical. Closing price of the first day less the offer price is calculated according to the method adopted by Aggarwal, Leal, and Hernandez (1993), Chan, Wang, and Wei (2004) and Chi and Padgett (2005). The returns are weighted equally across the board.

$$RIPO = \left(\frac{P_{i1} - P_{i0}}{P_{i0}} \right) \qquad (15)$$

where $P_{i1} =$ the first day closing price, $P_{i0} =$ the offer price.

The Consumer Sentiment Index (CSI)

In addition to the indirect proxies of investor sentiment in line with studies by Baker and Wurgler (2006; 2007), the widely-adopted consumer sentiment index that measures household perceptions of the general economy is also included as one of the proxies to measure investor sentiment. The consumer sentiment index is published by the Malaysian Institute of Economic Research (MIER). As the index is currently available on a quarterly basis, it is interpolated into monthly intervals using the cubic spline method in order to maintain consistency with other variables. A method that is popular among economists applied on inconsistent frequency of financial data, cubic spline interpolation estimates values with a mathematical function with the advantage to minimise overall surface curvature, resulting in a smooth surface that passes exactly through the input points.

4.3 Methodology and Analysis

This section describes the research methodology that tests each of the hypotheses described in Chapter Three. It commences with descriptive analysis and continues with causal relationship tests.

4.3.1 Descriptive Analysis

The descriptive data analysis and interpretation component of the study is intended to summarise the main features of the data. The analysis includes calculation of means, deviation, skewness, and extreme values of the variables, which play a vital role in supporting inferential statistics. The variables include macroeconomic variables, prices of the KLCI, and proxies for investor sentiment. The initial analysis also includes unit root test in order to determine the stationarity of data. Upon obtaining the findings, the relationship of the variables is tested to meet the research objectives.

Root Test and Co-integration

Apart from the descriptive analysis that tests the mean, median, and normality of each series, the data analysis also tests stationarity in the mean of the series. It is essential, as many economic and financial time series are widely known to exhibit trending behaviour or non-stationarity in the mean. Common examples are asset prices, exchange rates, and the levels of macroeconomic aggregates like real GDP. Therefore, it is an important econometric task to determine the most suitable form of the trend in the data.

For instance, ordinary least square modelling requires the data to be converted to stationary form prior to analysis. Therefore, some form of trend removal is required if the data are trending. The two well-known de-trending or trend removal procedures are first differencing and time-trend regression; first differencing is applicable for I(1) time series and time-trend regression is appropriate for trend stationary I(0) time series. In addition to economic and finance theories that suggest the existence of long-run equilibrium relationships among non-stationary time series variables, unit root tests can also be used to determine if trending data need to be first-differenced or regressed on deterministic functions of time to reduce data stationarity (Engle and Granger, 1987). In the presence of I(1) variables, co-integration techniques can be used to model long-run relationships. Therefore, the first step prior to co-integration modelling is pre-testing for unit roots.

For the purpose of this study, each series are tested for unit root via the augmented Dickey-Fuller and Phillips-Perron tests using EViews 8 software. The Dickey-Fuller (DF) tests involve fitting a regression of ordinary least squares:

$$Y_t = \alpha + \rho_{t-1} + \delta_t + u_t \qquad (16)$$

To account for serial correlation, the augmented DF test's regression includes lags of the first differences of Y_t. On the other hand, the Phillips-Perron (PP) test is made robust to serial correlation by using Newey and West's (1987) bandwidth.

4.3.2 Causal Studies: (RQ1) The Relationship Between Macroeconomic Fundamental Variables and the Volatility of Stock Returns During (i) the Whole Period of Study (2000-2012) and (ii) the 2008 Global Financial Crisis

This section embarks on the testing of Hypotheses 1 (i) and 1 (ii), which examine the relationship between macroeconomic fundamentals and Malaysian stock market volatility. The independent variables include the BLR, CPI, IPI, M3, and the EER; while the dependent variable is the volatility of KLCI returns, whose measurement was introduced by French, Schwert, and Stambaugh (1987). Details of the methodology will be discussed in the later part of this chapter. As widely practised in studies of econometrics, each variable is transformed into normal logarithm to enhance normality of the data and to test for the existence of unit roots. Next, the vector autoregressive model (VAR) is applied as it provides dynamic statistical representations of past interactions between the variables. Developed by Sims (1980), VAR is a dynamic system of equations in which the current level of each variable depends on past movements in that variable and in all the other variables in the system.

As the selection of models to identify a relationship relies on the characteristics of the variables concerned, the application of an alternative model is unavoidable. In this respect, Autoregressive Distribution Lags (ARDL) is selected as a possible method to complement VAR in modelling the relationship. In contrast to VAR, ARDL allows dynamic relationships between variables of different levels of integration, while VAR requires all variables to be at the same level of integration.

Vector Autoregressive Modelling (VAR)

Estimating VAR involves deciding on the number of lags, which is usually determined by statistical criteria such as sequential-likelihood ratio tests and Akaike or Schwartz information criteria. However, since coefficients of VAR models are atheoretical in nature, hence difficult to interpret, a feature of VAR that tests for the direction of causality developed by Granger (1969) is adopted. It allows traces of the effect of a one-time shock to current and future values of endogenous variables through the generalised impulse response function developed by Pesaran and Shin (1998). Well known for testing causality, Granger causality is a relatively simple test that defines causality, for instance, between macroeconomic variables or the investor sentiment composite index and stock market volatility. Stock market volatility can be predicted with greater accuracy by using past values of macroeconomic fundamentals or the consumer sentiment index, provided all other terms remain unchanged.

The Vector Error-Correction Model (VECM)

Once VAR variables are co-integrated, vector error-correction (VEC) is modelled. Error-correction model is a dynamic system where the deviation of the current state from its long-run relationship is fitted into its short-run dynamics (Engle and Granger, 1987). The VEC model is given by:

$$\Delta Y_t = \beta_{y0} + \beta_{y1}\Delta y_{t-1} + \ldots + \beta_{yp}\Delta y_{t-p} + \gamma_{y1}\Delta x_{t-1} + \ldots + \gamma_{yp}\Delta x_{t-p} - \lambda_y(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}) + v_t^y \qquad (17)$$

$$\Delta x_t = \beta x_0 + \beta x_1 \Delta y_{t-1} + \ldots + \beta_{xp}\Delta y_{t-p} + \gamma_{x1}\Delta x_{t-1} + \ldots + \gamma_{xp}\Delta x_{t-p} - \lambda_x(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}) + v_t^x \qquad (18)$$

where $y_t = \alpha_0 = \alpha_1 x_t$ is the long-run co-integrating relationship between the two variables, and λy λ_x are the error-correction parameters that measure how *y* and *x* react to deviations from the long-run equilibrium. However, it is well known that VECM is only valid if the variables are in the same order of integration, i.e., I(1). When the variables are not in the same order of integration, the Autoregressive Distributed Lags (ARDL) model is employed. The latter provides an alternative approach to test the long-run relationship.

Autoregressive Distributed Lags Model (ARDL)

Traditionally, the ARDL (p,q) model is known for modelling the analysis of long-run relationships when the underlying variables are integrated of order one. In more recent studies, ARDL (p,q) also holds the advantage that it yields consistent results regardless of whether the underlying variables are integrated of order zero, one, or a combination of both (Pesaran, Shin, and Smith, 2001; Pesaran and Shin, 1997). The ARDL (p,q) model for analysing long-run relations when the underlying variables contain I(1) regressors and deterministic trend is as follows:

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \phi_i y_{t-i} + \beta x_t + \sum_{i=0}^{q-1} \beta_i \Delta x_{t-1} + u_t \qquad (19)$$

$$\Delta x_t = P_1 \Delta x_{t-1} + P_2 \Delta x_{t-2} + \ldots + P_s \Delta x_{t-s} + \varepsilon_t \qquad (20)$$

where x_t is the k-dimensional I(1) variable that is not co-integrated. u_t and ε_t are serially uncorrelated with zero means and constant variance-co-variances. P_i are $k \times k$ coefficient matrices such that the vector autoregressive process in Δx_t is stable. Pesaran et al. (2001) also developed a new bound approach that tests the existence of a level relationship between variables whose levels of stationarity are uncertain. To test the significance of lagged levels of variables under deliberation in a conditional equilibrium correction model (ECM), the commonly used Wald or F-statistic in a generalised Dickey-Fuller type regression is used. The simulation result from ARDL modelling estimated by

Pesaran et al. (2001) shows that this procedure can be reliably tested in small samples for long-run coefficients where the essential variables are I(0) or I(1). Further details of the ARDL (p,q) model are discussed in Chapter Five. Both VECM and ARDL (p,q) models are employed to test the first statistical hypothesis:

Macroeconomic fundamentals (BLR, CPI, IPI, M3, and EER) have no significant causal effect on the volatility of the KLCI.

This hypothesis tests two specific periods: (i) the whole period of study (2000-2012), and (ii) the sub-period of the global financial crisis. This leads to the construction of a parsimonious model:

$$VKLCI_t = \alpha_0 + \Sigma\alpha_2 BLR_{t-j} + \Sigma\alpha_3 CPI_{t-j} + \Sigma\alpha_4 IPI_{t-j} + \Sigma\alpha_5 M3_{t-j} + \Sigma\alpha_6 EER_{t-j} + \varepsilon_t \tag{21}$$

where $VKLCI_t$ is the volatility of KLCI at time t; $BLR_{t\text{-j}}$ denotes the interest rate at designated time lags; CPI_{t-j} denotes the inflation rate at designated time lags; IPI_{t-j} denotes the industrial production growth at designated time lags; $M3_{t-j}$ denotes the growth of money supply at designated time lags; EER_{t-j} denotes the exchange rate at designated time lags, and ε_t denotes the error term.

4.3.3 Determination of the 2008 Global Crisis Period

In determining the global crisis period, the period of study is divided into a specific focus of investigation. There are a number of methodologies to determine the structural breaks. One of methodologies is the measurement introduced by Chow (1960). This classic test requires estimation of two sub-period models where the equality of the periods is tested using an F-statistic. However, the disadvantage of this method is that the break date must be known *a priori*. Recently, a more effective methodology has been introduced, where multiple structural breaks can be detected without prior knowledge of the dates. This method is known as Bai-Perron's multiple structural test (Bai and Perron, 1998; 2003a; 2003b); it allows multiple unknown breakpoints. In this analysis, the double maximum test is selected where the null hypothesis without structural breaks is tested against an unknown number of breaks. This test uses the equal weight version where estimates of the breakpoints are obtained using global maximisation of the sum squared residuals.

This method requires the errors to be serially uncorrelated. In order to construct the optimal bandwidth or HAC estimator, each element of the vector is estimated with quadratic spectral kernel with AR(1). This methodology identifies several structural breaks throughout the 13-year period of study, whereby the suggested structural break coincides with the 2008 global financial crisis.

4.3.4 Causal Studies: (RQ2) The Relationship Between the Investor Sentiment Composite Index and the Volatility of Stock Returns During (i) the Whole Period of Study (2000-2012), and During (ii) the Sub-period of the Global Financial Crisis

The next section details the methodology employed in testing relationships between investor sentiment and stock market volatility for hypotheses 2 (i) and 2 (ii). The independent variable is the constructed investor sentiment composite index, while the dependent variable is the volatility of KLCI modelled by GARCH or as calculated by adopting French et al.'s (1987) volatility measure. As with the first research question in subsection 4.3.3, both VECM and ARDL (p,q) models are employed to test the first statistical hypothesis:

The investor sentiment composite index has no significant causal effect on the volatility of the KLCI.

This hypothesis tests the two specific periods: (i) the whole period of study (2000-2012), and (ii) the sub-period of the global financial crisis. This leads to the construction of a parsimonious model:

$$VKLCI_t = \alpha_0 + \Sigma\alpha_1 ISCI_{t-j} + \varepsilon_t \qquad (22)$$

where $VKLCI_t$ is the volatility of KLCI at time t; $ISCI_{t\text{-}j}$ denotes the investor sentiment composite index at designated time lags; and ε_t denotes the error term. However, as there is no significant single measurement available in the local stock market, this study proposes the construction of an investor sentiment composite index to represent the sentiment in the Malaysian stock market. The following section describes the construction of the investor sentiment composite index by adopting factor analysis with principal component analysis extraction.

Construction of the Investor Sentiment Composite Index

In constructing the composite index, it is essential to set up the data input. Since the variables or proxies proposed in this study are measured in different units, they are generally not additive. In order to overcome the flaw, prior to running the data to factor analysis, each of the series is converted into comparable units in such a way that the initial scale chosen for measuring them does not bias the results. In doing so, each series is standardised to obtain zero mean and unit variance by subtracting the mean and dividing by the standard deviation in each case. The method adopted to standardise the variable is described below:

$$\chi_{ij} = (Xi_j - X_m / \sigma) \qquad (23)$$

where χi_j denotes free-scale observation; Xi_j denotes the original observation; X_m denotes the mean of the series, and σ represents the standard deviation of the series.

The next step is to transform each proxy in logarithm. Logarithmic transformations are very popular in econometrics due to several reasons. First, many economic time series exhibit strong trends caused by some underlying growth process. A plot of the series normally reveals an exponential curve. Taking the natural logarithm of such series thus effectively linearises the exponential trends. Secondly, logs may also be used to linearise a model which is non-linear in parameters in order to be easily estimated by using ordinary least squares (OLS) regression.

The possible measures of investor sentiment in the Malaysian stock market are: the proxy of stock market liquidity, the proxies of initial public offerings, the advance/decline ratio, and the consumer sentiment index published by MIER. A composite index that represents all proxies discussed under the above section will be constructed based on the common variation in the 5 underlying proxies for sentiment. Each observed proxy is assumed to have a positive relationship with the underlying sentiment. These are: stock market turnover, number of initial public offerings, average first day returns, the advance/decline ratio, and the consumer sentiment index. The sentiment proxies are measured in monthly frequency from 2000-2012. A similar strategy by Baker et al. (2012) and Baker and Wurgler (2006; 2007) on New York Stock Exchange sentiment is adopted for this study. Nonetheless, in constructing a composite index, a couple of issues need to be addressed: firstly, it is observed that idiosyncratic, non-sentiment related components are inevitably embedded in each sentiment proxy.

Therefore, in order to isolate the common component from all the proxies, factor analysis using principal component analysis (PCA) extraction in determining the factors is adopted, as introduced by Baker and Wurgler (2006; 2007) and Brown and Cliff (2004). The purpose of principal component analysis is to determine factors in such a way as to explain as much of the total variation in the data as possible with as few factors as possible. Secondly, some proxies may possess a month's lag or lead relative to other proxies which correlate to the common component of investor sentiment composite index.

It is known that most financial markets are characterised by a high level of co-linearity in returns. Co-linearity is when the returns process reveals an excessive level of correlation due to only a few important sources of information in the data, and this information being common to many variables. To overcome the issue, Principal Components Analysis (PCA) is adopted as a method to extract the most important uncorrelated bases of information in the data (Alexander, 2001). Its objective is to condense the dimensionality of the problem so that only vital sources of information are used. This is done by extracting only the first *m* principal components.

PCA defines a projection that summarises a set of data with maximum variation and segregates them orthogonally. By doing this, highly correlated data can be independently explained by just a few principal components that share similar underlying characteristics. The objective of this system is to find the eigenvectors of the correlation matrix. The directions of the principal components of the original data – their statistical significance – is given by their corresponding eigenvalues. Multiplication of the original value matrix with the eigenvalue matrix produces the principal components. In other words, it is a regression of the original series and a small number of principal components. Hence, a reduction of dimensionality is implemented, and only a small number of components having the largest variance are retained. At this point, the highest variance explains a more robust estimation of co-variance matrix from the original data (Rachev, Mittnik, Fabozzi, Focardi, and Jasic, 2007).

The series that estimates the highest variance are therefore grouped into the first principal component, which is also regarded as a single axis. Data that are in excess are then grouped as second and third principal components which are perpendicular to the first two principal components. As a rule of thumb, the data prior to inclusion in the PCA must be stationary. Since rates, prices or yields are normally non-stationary, they should be transformed into common returns before the application of PCA (Alexander, 2001). This is because different results are obtained in different units if PCA is applied to prices instead of returns. In these cases it might be preferable to apply the PCA technique to the correlation matrix (Rachev et al., 2007).

The second issue is the relative timing of the variables in terms of determining the leads and lags of the variables which reflect a given shift in sentiment earlier than other variables (Brown and Cliff, 2004; 2005). All variables are log transformed to be consistent with normal distribution assumptions, converting prices to returns. However, the decision to define which series to include in the analysis, is the timing factor. Some variables may reflect the same shift in sentiment before others. In general, proxies that involve firm supply decisions are further down the chain of events, and are likely to lag behind proxies based directly on investor trading pattern on prices. The first step is to estimate the first principal components of the 5 proxies and their lags, creating a first stage index with 10 loadings, one for each of the current and lagged proxies.

The measure of sampling adequacy is determined by the Kaiser-Meyer-Olkin (KMO) value. The rule of thumb is that a KMO value between the range of 0.5 to 1.0 is appropriate for the use of principal component analysis (Hair, Black, Babin, and Anderson, 2009). Subsequently, the correlation between the first stage index and the current and lagged values of each of the proxies are computed to estimate how much information will be lost if the 5 terms are dropped with other time subscripts. The first principal component of a set of time series variables is the linear combination of the variables with the coefficients chosen to capture as much of the joint variation across the series as possible. Finally, the construction of the sentiment index comprises the first principal component of the correlation matrix of 5 variables, where each respective proxy's lead or lag depends on the strength of correlation with the first stage index.

This procedure leads to a parsimonious sentiment index:

$$Sent_{p,t} = \beta_1 liquidity_t + \beta_2 advdec_t + \beta_3 nipo_t + \beta_4 ripo_t + \beta_6 CSI_t \tag{24}$$

where each of the index components has first been standardised. The index is expected to iron out extreme observations. All 5 proxies are expected to contribute positive signs towards the constructed sentiment index. The coefficient values determine the importance of the relationship between the variables and the index, apart from the direction. The index is then plotted to observe the common features between sentiment and (local or global) macroeconomic conditions. However, equation (24) may be seen as a measure of investor sentiment given that it might include a common fundamental macroeconomic effect as opposed to a sentiment component. The purpose is to capture the variation of these variables of non-rational reasons that do not vary with business cycles.

Therefore, a second index is constructed to explicitly remove business cycle variation from each of the proxies prior to the principal component analysis, thus reducing the likelihood that these proxies are connected to fundamental systematic risk. Specifically, each proxy is regressed on the monthly series interest rates (BLR), inflation rates (CPI), exchange rates (EER), industrial production index (IPI), and broad money supply of the country (M3).

Hence, cleaner proxies for investor sentiment are represented by the residuals, labelled with a superscript *C* from the regressions. The first principal component explains the highest variations of the cleaner variables, thus retaining all of the appealing properties of sentiment. An index of the cleaner proxies is constructed using the same procedure. The resulting index is:

$$Sent_t^C = \beta_1 liquidity_t^C + \beta_2 advdec_t^C + \beta_3 nipo_t^C + \beta_4 ripo_t^C + \beta_5 CSI_t^C \tag{25}$$

The cleaner proxy (which is net economic factors) is expected to have significant predictive power for aggregate stock market volatility. As part of robustness measure, the model is controlled with macroeconomic variables and the 2008 global financial crisis. This determines the sustainability of the investor sentiment composite index as a good predictive variable of stock market volatility in Malaysia.

4.3.5 Robustness Test: (RQ3) The Relationship between the Investor Sentiment Composite Index and Stock Market Volatility Controlled by (i) Macroeconomic Fundamentals and (ii) the Sub-period of the Global Financial Crisis

This subsection tests the hypotheses that employ BLR, CPI, IPI, M3, EER, the investor sentiment composite index, and the 2008 global financial crisis as independent variables. The volatility of KLCI is treated as the dependant variable. In extension of the previous step in testing the robustness of the investor sentiment composite index, it is important to include macroeconomic variables and the 2008 global financial crisis as control variables. This step is crucial in order to determine whether these variables significantly maintain their predictive value with the inclusion of the control variables. The econometric model adopted here is ARDL (p,q) basic model and ARDL (p,q) bound testing for variables from different order integrations. Similar hypothesis 2(i), the independent variables included are the newly-constructed investor sentiment composite index, and all five macroeconomic fundamentals are treated as control variables. For subsequent hypotheses, we test whether the newly-constructed investor sentiment composite index maintains its predictive value relative to the volatility of the KLCI with the inclusion of the global financial crisis. In this process, the period of the global crisis is treated as a dummy. Additionally, the relationships are tested at different lags to determine the predictive values. Hence, the third hypothesis tests:

Investor sentiment has no significant effect on the volatility of the Malaysian stock market when controlled by macroeconomic fundamentals and the global financial crisis.

As with hypotheses 1 and 2, the VAR and ARDL (p,q) models are employed in order to examine the relationship. Hence, the expected parsimonious model is as follows:

$$VKLCI_t = \alpha_0 + \Sigma\alpha_1 ISCI_{t-j} + \Sigma\alpha_2 BLR_{t-j} + \Sigma\alpha_3 CPI_{t-j} + \Sigma\alpha_4 IPI_{t-j} + \Sigma\alpha_5 M3_{t-j} + \Sigma\alpha_6 EER_{t-j} + \varepsilon_t \qquad (26)$$

$$VKLCI_t = \alpha_0 + \Sigma\alpha_1 ISCI_{t-j} + D_{globalcrisis} + \varepsilon_t \qquad (27)$$

where $VKLCI_t$ is the volatility of KLCI at time t; $ISCI_{t\text{-j}}$ denotes the investor sentiment composite index at designated time lags; $BLR_{t\text{-j}}$ denotes the interest rate at designated time lags; CPI_{t-j} denotes the inflation rate at designated time lags; IPI_{t-j} denotes the industrial production growth at designated time lags; $M3_{t-j}$ denotes the growth of money supply at designated time lags; EER_{t-j} denotes the exchange rate at designated time lags; $D_{globalcrisis}$ denotes the dummy variable for the global financial crisis period; and ε_t denotes the error term for the model. Table 4.1 summarises the measurement variables and methods that are used to analyse each research question. A more thorough discussion of the research methodology in analysing research questions will be presented in Chapter Five.

Table 4.1 List of Procedures and Analytical Methods

Research Questions	Variables	Analytical Method
RQ1: Are macroeconomic fundamentals sufficient to predict the volatility of the Malaysian stock market during (i) 2000-2012, and (ii) the sub-period of the global financial crisis?	IV: BLR, CPI, IPI, M3, and EER DV: volatility of KLCI	1) Descriptive analysis 2) Standard deviation measure of volatility 3) VAR with Granger causality 4) VECM 5) ARDL (p,q) bound test model
RQ2: Does investor sentiment predict the volatility of the Malaysian stock market during (i) 2000-2012, and (ii) the sub-period of the global financial crisis?	IV: Investor sentiment composite index DV: volatility of KLCI	1) Descriptive analysis 2) Correlation analysis 3) Principal component analysis 4) ARDL (p,q) models
RQ3: Do (i) macroeconomic fundamentals and (ii) the sub-period of the global financial crisis affect the predictability of investor sentiment relative to Malaysian stock market volatility?	IV: Investor sentiment composite index DV: Volatility of KLCI Control variables: BLR, CPI, IPI, M3, and the EER; 2008 global financial crisis	1) VAR model with Granger causality 2) ARDL (p,q) bound test model

4.4 Summary

This chapter began with an overview of the theoretical paradigm underlying this study. It described secondary data retrieved from various sources to represent the variables concerned. The data and methodology section described the tools to be applied in achieving stated research objectives and answering the research questions delineated during the initial part of the thesis proposal. In constructing the investor sentiment composite index, factor analysis with principal component analysis will be used with multiple approaches. Results from the analyses will be compared in order to get the best possible index to represent the investor sentiment of Bursa Malaysia. Next, several hypotheses will be tested in order to examine the relationships among and the effect of independent variables that consist of macroeconomic variables and the investor sentiment composite index. The following chapter presents the empirical findings of the study followed by a discussion of results.

CHAPTER 5: ANALYSIS

5.1 Introduction

This chapter provides necessary statistical analyses in order to meet the objectives of this study, and to test the hypotheses discussed in Chapter Four. The summary of analyses will be furnished at the end of the chapter. The first section commences with descriptive analysis leading to causal studies between macroeconomic fundamentals and volatility of the Malaysian stock market. It continues with modelling the volatility of the Kuala Lumpur Composite Index (KLCI) and finally testing the causal relationship between investor sentiment and stock market volatility. As mentioned in Chapter One, one of the challenges in this study is the absence of a unanimously accepted measurement of investor sentiment. Thus, another important aim of this study is to construct a composite index for investor sentiment relevant to the Malaysian stock market. Next, the causal relationship between stock market volatility during periods of crisis and macroeconomic fundamentals and sentiment index are also examined. Finally, in order to perform robustness checks for the constructed investor sentiment composite index, this study conducts numerous tests to examine the predictive power of the composite index relative to the volatility of stock market returns, controlled by the global financial crisis as well as macroeconomic fundamentals.

Descriptive Statistics

This section presents the descriptive statistics of each macroeconomic variable in order to answer the first research question. This is a fundamental step prior to determining a method appropriate to model the relationship between macroeconomic variables and the volatility of stock market returns. The macroeconomic variables are: base lending rates (BLR) which represent interest rates, consumer price index (CPI) which represents the rate of inflation, industrial production index (IPI), broad money measure (M3), and effective exchange rate (EER). The dependent variable is the volatility of the well-known KLCI. All series are log-transformed to linearise the data as well as to simplify interpretation of results. Table 5.1 shows the descriptive results of the five independent variables which affect the volatility of KLCI. As a reference to the selection of variables for following analyses, a comparison between unlogged (raw) data and logged transformed data is also made.

With reference to results of the raw series in Table 5.1, M3 has the largest statistic value of mean, median, maximum and minimum values of the series. Apparently, CPI holds the only negative minimum value in this series. The assessment of normality for each data series is seen from the descriptive statistics. The statistics report skewness and kurtosis that measure the asymmetry and peakedness of the distribution. Row 6 in Table 5.1 shows that only BLR, CPI, and IPI are negatively skewed. CPI is platykurtic relative to the normal in terms of its peakedness. By and large, the Jarque-Bera test of normality of distribution (Jarque and Bera, 1980) confirms that residuals from all variables (except EER) come from non-normal distribution data. This is justified by the significance of the statistic at 1%, hence rejecting the null hypothesis that the series are normally distributed.

Table 5.1 Descriptive Statistics (Raw and Log-transformed) of BLR, CPI, EER, IPI, M3, and KLCI

	RAW SERIES						LOG TRANSFORMED SERIES					
	BLR	CPI	EER	IPI	M3	KLCI	LBLR	LCPI	LEER	LIPI	LM3	LKLCI
Mean	6.352	1.806	98.475	97.441	773302	1051	0.802	0.814	1.993	1.985	5.861	6.911
Median	6.390	1.700	98.505	100.700	703062	928	0.806	0.824	1.993	2.003	5.847	6.833
Maximum	6.790	7.200	106.910	119.800	1352886	1689	0.832	1.087	2.029	2.079	6.131	7.432
Minimum	5.510	-4.500	91.670	69.710	434711	573	0.741	-0.286	1.962	1.843	5.638	6.351
Std. Dev.	0.379	1.599	3.441	12.901	274316	321	0.027	0.157	0.015	0.060	0.153	0.305
Skewness	-0.696	-0.257	0.246	-0.510	0.504	0.397	-0.791	-4.189	0.175	-0.653	0.120	0.075
Kurtosis	2.492	7.960	2.423	1.959	2.061	1.824	2.692	26.498	2.373	2.118	1.708	1.764
Jarque-Bera	14.286***	161.66***	3.733	13.802***	12.332***	13.081***	16.889***	4045***	3.354	16.146***	11.225***	10.08***
Observations	156	156	156	156	156	156	156	156	156	156	156	156
ADF:												
with drift	-2.519	-3.844***	-2.185	-1.166	4.427	0.225	-0.975	-3.246**	-1.804	-2.588*	1.5609	-0.521
with drift and trend	-2.436	-3.844**	-2.179	-1.856	-0.965	-2.589	-1.899	-3.27*	1.821	4.905***	-3.244	-3.162*
without drift and trend	-0.29	-2.471**	0.241	1.426	11.117	1.374	0.701	-0.601	0.572	-0.691	10.73	1.037
PP:												
with drift	-2.216	-3.511***	-2.124	-1.99	4.102	-0.193	-0.902	-3.582***	-2.125	-2.097	1.428	-0.521
with drift and trend	-2.107	-3.442**	-2.143	-5.452	-1.015	-2.869	-1.805	-3.6039***	-2.143	-5.081	-3.244	-3.162
without drift and trend	0.296	-2.228**	0.431	1.846	10.381	1.007	0.802	-0.558***	0.492	2.127	10.23	0.845

Note: ***, **, and * denote the significance level of 1%, 5%, and 10% respectively. BLR represents base lending rate. CPI represents consumer price index. EER represents effective exchange rate. M3 represents broad money supply. KLCI represents Kuala Lumpur Composite Index. J.B is the Jarque-Bera test of normality. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are applied for unit root test.

Comparisons are also made between the raw series and log-transformed series of the macroeconomic variables in order to examine the difference that log-transformation makes to each variable. This method is expected to minimise the non-normality distribution of the data. However, with reference to Table 5.1, the Jarque-Bera statistic shows that there are only minor increases of normality in log-transformed series relative to the raw series – meaning that the positive skewness of each series is slightly removed with the transformation. As evident from the results for kurtosis, only EER seems to show reduction in peakedness. This is consistent with the Jarque-Bera statistic that only EER and LEER are from normal distributions. Although almost all data are from non-normal distribution, violation of the normality assumption should not be a major concern for a large sample size (n>30) (Pallant, 2007).

Unit Root Testing

The stationary of residuals of the series are examined with the augmented Dickey-Fuller (Dickey and Fuller, 1979) and Phillip-Perron (Phillips and Perron, 1988) tests. This step is necessary prior to applications of later parametric analyses. Both tests investigate the null hypothesis that there is a unit root in the series. The unit root is tested as pure random walk, either with drift or with drift and time trend. The three models are thus tested for robustness in determining stationarity. Results show that both BLR and its log-transformed series contain evidence of unit root in all three models tested. CPI and its log-transformed series, on the other hand, are free of unit roots, and are therefore stationary in residuals. All three autoregressive models give significant results at 1% and 5% critical levels. The t-statistics for all models in their ADF and PP tests for EER show almost similar values, meaning that there is minor improvement through data log-transformation. However, IPI gained an improvement in residuals as reported by ADF, which shows significant values with drift and trend, weak significance for drift and its log-transformed series. Finally, M3 and KLCI remain non-stationary in residuals, both in raw and log-transformed series. As a remedy for the unit root problem, each series will be first or second-differenced prior to further parametric analyses. This is discussed in the causal relationship studies in following sub-sections.

The next step involves the modelling of volatility of the major stock market indicator, the KLCI. As mentioned in Chapter Four, two methods are applied to check for their robustness: the measurement of standard deviation introduced by French et al. (1987) and modelling the conditional volatility of ARCH and GARCH effect, if any.

5.2 Modelling the Volatility of KLCI

The first step in modelling the volatility of KLCI involves applying the measurement of volatility by French et al. (1987). The data are in monthly frequency that comprises of averaged daily values from 2000-2012. Since the measurement was described in Chapter Four, this chapter only discusses findings from the model. The computed standard deviations are converted into percentages in order to simplify the interpretation of results. This measurement highlights KLCI fluctuations observed from 2000-2012 (Figure 5.1). There are periods of high volatility from 2000 to 2001 and 2007 to early 2010. These periods concur with the Dot-com crisis, the September 2001 attack in the U.S, and the global financial crisis which started in late 2007.

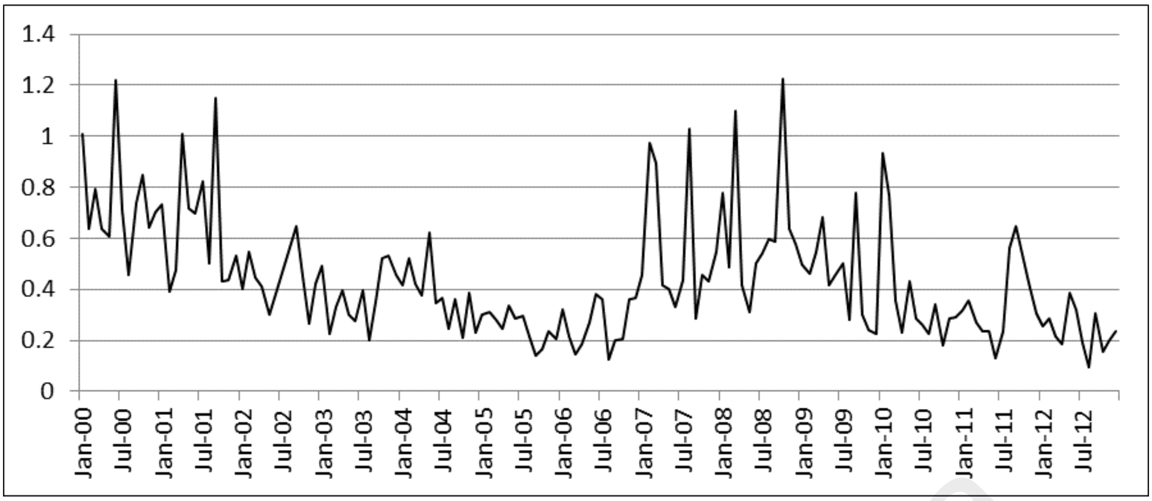


Figure 5.1 The Volatility of KLCI (VKLCI) from 2000-2012

Referring to Figure 5.1, the standard deviation of the KLCI seems to reach its highest point in October 2008 (1.225%), slightly surpassing the extreme volatility period of June 2000 (1.219%). The two periods coincide with the phenomenal crises which affected not only Malaysia but many countries throughout the globe. There are periods of tranquillity during the period of study, whereby minor fluctuations of KLCI were observed from October 2001 to August 2006, where the highest standard deviation is reported at 0.65%. The descriptive analysis of this measurement is shown in Figure 5.2 and Table 5.2. Figure 5.2 shows the histogram chart of the skewness and kurtosis of the measurement for volatility. The data is positively skewed (1.257) with the right-tail, which is consistent with Table 5.2.

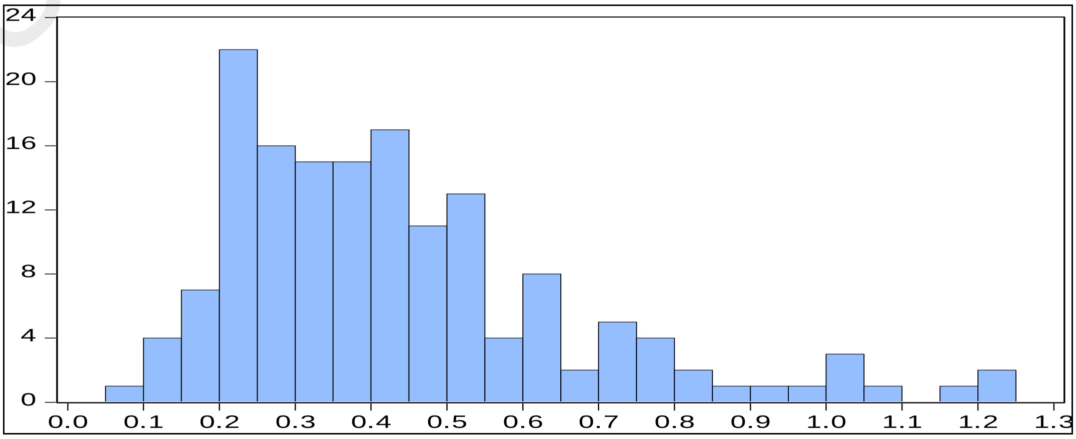


Figure 5.2 Histogram of Volatility

The mean of the data is 0.44%, with median number of 0.393, and maximum at 1.125%, while the data are at 0.233% dispersion from the mean. Apart from the statistic of skewness and kurtosis to test normality, the Jarque-Bera statistic is computed, and the results are given in Table 5.2. The hypothesis is that the data from non-normal distribution are rejected at the 1% level. Hence the volatility data are non-normal.

Table 5.2 Descriptive Statistics for the Measurement of Volatility (VKLCI)

	Results
Mean	0.440
Median	0.393
Maximum	1.225
Minimum	0.097
Std Dev	0.233
Skewness	1.257
Kurtosis	4.445
Jarque-Bera	54.63***
Observation	156

Note: *** denotes significance level of 1%.

A test to further accommodate the assumptions of parametric analyses is the stationarity of the series. The residuals of the series are tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. The ADF and PP test results as reported in Table 5.3 show that the residual series are free from unit roots except for the model without drift and trend.

Table 5.3 Unit Root Tests for the Measurement of Volatility

Unit Root Test	**T-statistic**	
	ADF	PP
with drift	-7.703***	-8.17***
with drift and trend	8.198***	-8.749***
without drift and trend	1.437	-2.834***

Note: *** denotes significance level of 1%.

This test reports results consistent with all three models. The hypotheses on series with unit roots are rejected at 1% significance level. Therefore, the series is consistently stationary at levels or I(0).

Figure 5.3 shows the daily movement of KLCI for the period of 13 years from the beginning of the new millennium. The fluctuations can be observed throughout the study period; a steep plunge is manifested during early 2009 from the impact of the U.S sub-prime crisis.

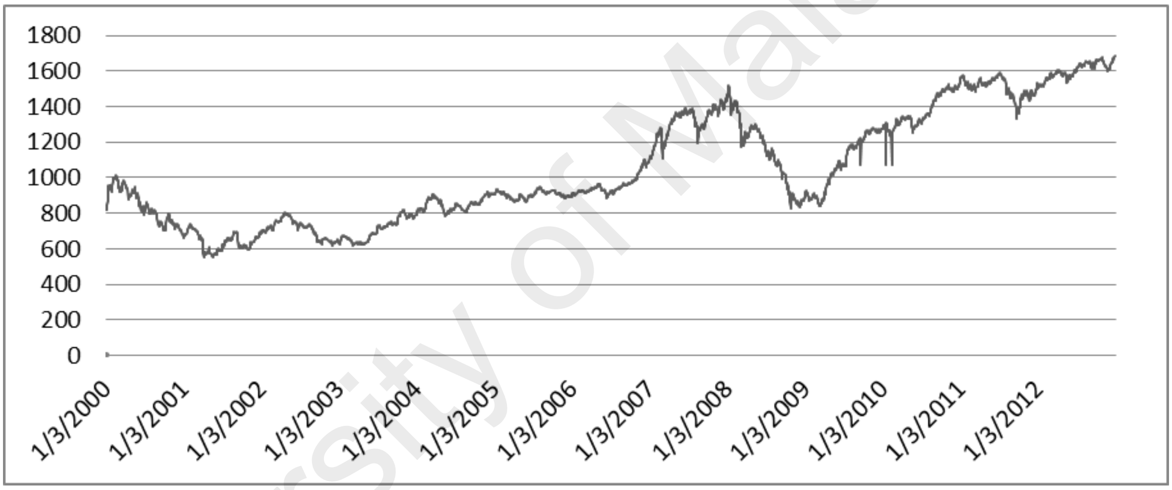


Figure 5.3 Daily KLCI Movement (2000-2012)

A smoother line is observed when the data are limited to monthly frequency (Figure 5.4). No significant changes in KLCI movement in monthly frequency are observed. Since the first half of 2009, an upward trend of the index is witnessed. Nevertheless, the plunge of KLCI can still be observed from late 2007 until the end of 2008 due to the U.S sub-prime crisis.

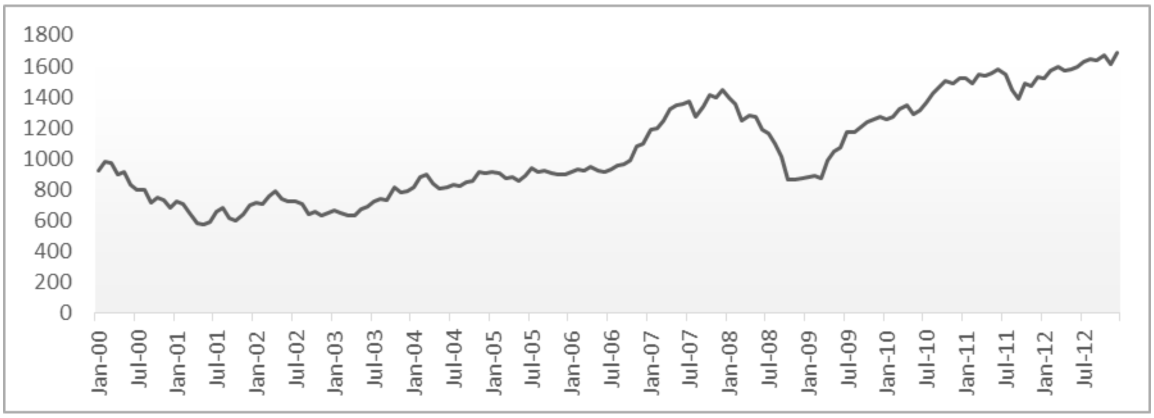


Figure 5.4 Monthly KLCI Movement (2000-2012)

In order to determine the justification of modelling the volatility of KLCI, the returns of the index in daily frequency are plotted as a mean of comparison. It is observed from Figure 5.5 that a number of periods of volatility clustered from 2007-2008. This means that there are certain periods with higher volatility, which are thus riskier than others.

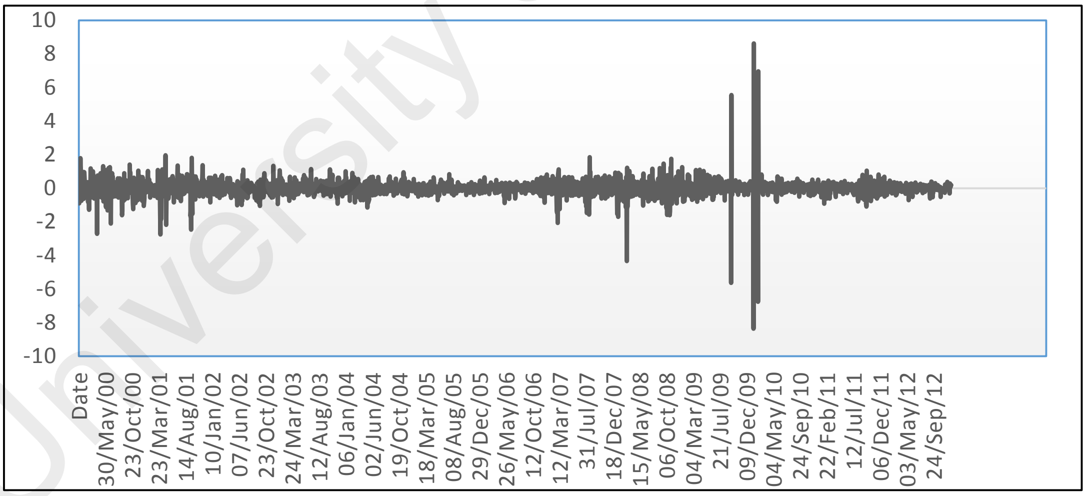


Figure 5.5 Daily Returns of KLCI (%) from 2000-2012

However, when returns are plotted in monthly frequency, the clustering of variances is subtle and insignificant (Figure 5.6). This is consistent with the existence of the ARCH effect on monthly data, as reported by Brailsford and Faff (1996) in their attempt to model the volatility of Australian stock market data. The evidence suggests that the ARCH and GARCH effects may be positively correlated with the frequency of data.

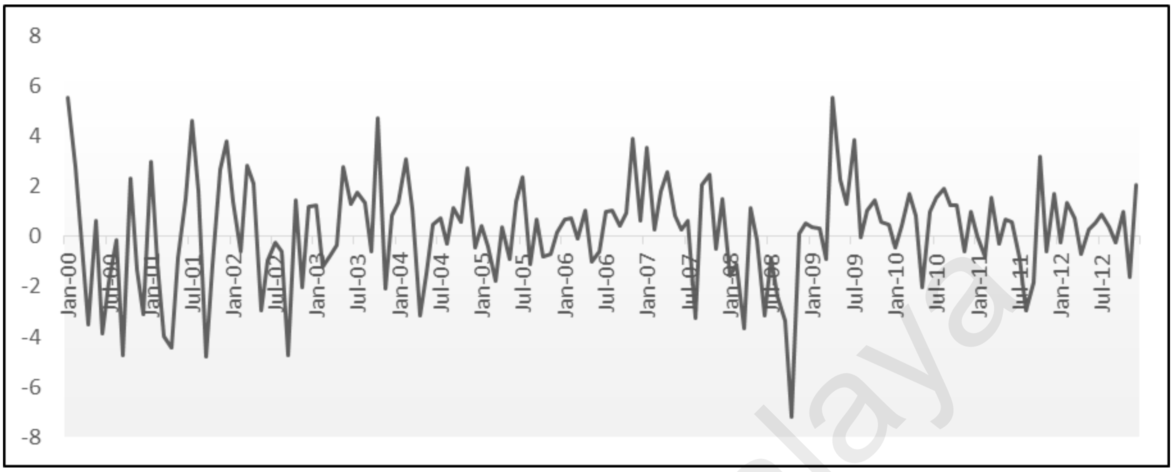


Figure 5.6 Monthly Returns of KLCI (%) from 2000-2012

The volatility of KLCI returns and consumer sentiment indices are therefore modelled with ARCH and GARCH conditional volatility modelling techniques. Further analyses are conducted to observe the significance of macroeconomic variables to explain the behaviour of stock returns as well as stock volatility during the study period. This step is motivated by the findings of Angabini and Wasiuzzaman (2010), who modelled conditional volatility of KLCI returns as GARCH (1,1) for their daily frequency data.

To justify, KLCI monthly series data are tested in comparison with daily frequency returns. This basic step investigates the possible presence of an ARCH effect in order to determine whether the model requires the ARCH estimation method instead of ordinary least squares (OLS). The Breusch-Pagan-Godfrey test is applied to the KLCI returns series. The results are shown in Table 5.4, whereby the null hypothesis is that there is no heteroscedasticity in the series. The statistic null hypothesis is stated as: $H_0 : \gamma_0 = \gamma_1 = \lambda_2 = ...\lambda_q$

Table 5.4 Estimation of ARCH Effect on KLCI Returns

Heteroscedasticity Tests	Data Frequency	TR^2
Breusch-Pagan-Godfrey	Daily	102.28***
	Monthly	2.90*
ARCH	Daily	41.939***
	Monthly	0.0009
Glejser	Daily	4.68**
	Monthly	2.908

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. TR^2 test statistic follows a χ^2 distribution with q degrees of freedom.

The series is first examined for the presence of an ARCH effect. Applying the Breusch-Pagan-Godfrey test, ARCH (1) gives a TR^2 value of 102.28, which is evidence of an ARCH effect in daily KLCI returns. Results from the three tests of heteroscedasticity – namely, Breusch-Pagan-Godfrey, ARCH, and Harvey and Glejser – are consistent with the volatility clustering behaviour of KLCI returns (Figure 5.5). For monthly returns, only the Breusch-Pagan-Godfrey test evidences a significant test result. ARCH and Glejser heteroscedasticity tests provide consistent evidence of homoscedasticity of variance in monthly returns residuals. Both results are highly significant at the 1% level. It is observed that as the frequency of data gets lower, the ARCH effect reaches almost non-existence in the residuals of KLCI returns. The findings do not justify the modelling of monthly KLCI returns with GARCH (1,1) by Zakaria and Shamsuddin (2012).

Although daily returns may have all the evidence pointing towards the decision to model the variances with ARCH, the daily frequency data of KLCI returns will not be adopted for further testing in this study. This is because other variables adopted in this study – including macroeconomic variables – are only available in monthly frequency. Therefore, due to consistency with the independent variables, KLCI returns in monthly frequency are the best possible candidate for further analyses. However, since heteroscedasticity tests show no significant ARCH effect in the residuals of the series in monthly frequency, this method of measuring volatility is inevitably rejected, and therefore the volatility measure by French et al. (1987) will be adopted for further analyses.

To recapitulate, this section analysed the descriptive statistics for each of the variables involved in the testing of relationships in Section 5.3. The dependent variable in this study is the volatility of KLCI, which is computed by the standard deviation introduced by French et al. (1987). The independent variables are the log-transformed values of BLR, CPI, IPI, EER, and M3. In order to meet the first objective of this study and to answer the first research question, the next section describes the relationship between macroeconomic variables and the volatility of KLCI as established by research question 1.

5.3 Macroeconomic Fundamentals and the Volatility KLCI

5.3.1 The Whole Period of Study (2000-2012) [RQ1(i)]

This section begins with the examination of correlations between the variables and ends with the study of causal relationships between variables modelled by VAR, VECM, and ARDL (p,q). Since most of the variables are non-stationary, non-parametric statistical correlation analysis (Spearman’s rank-order correlation) is adopted. The results of the correlations between the macroeconomic fundamentals are shown in Table 5.5.

Table 5.5 Correlations between BLR, CPI, EER, IPI, M3, and VKLCI

	BLR	CPI	EER	IPI	M3	VKLCI
BLR	1					
CPI	0.325***	1				
EER	0.414***	0.117	1			
IPI	-0.022	0.094	-0.083	1		
M3	-0.229**	-0.014	-0.052	0.867***	1	
VKLCI	0.361***	-0.091	0.053	-0.348***	-0.369***	1

Note: *** and ** denote significance levels of 1% and 5% respectively.

As illustrated in Table 5.5, it is evident that BLR, IPI, and M3 are significantly correlated with the volatility of KLCI. Findings indicate that VKLCI has significant positive co-movement relationship with BLR by 0.36. Nevertheless, IPI and M3 are inversely correlated with the VKLCI; both relationships being significant at the 1% critical level. The results evidently support further analysis of the relationship between the variables, specifically in searching for the explanatory variables of VKLCI. Next, the predictive value of each of the macroeconomic variables on the volatility of the KLCI is examined. In doing so, it is crucial to determine the appropriate technique to model the relationships. The first main statistical hypothesis is:

H1(i): Macroeconomic fundamentals (BLR, CPI, IPI, M3, and EER) have no significant causal relationship with the volatility of the KLCI

The hypothesis tests two specific periods: (i) the whole period of study (2000-2012) and (ii) the sub-period of the global financial crisis.

Vector Autoregressive Model (VAR) Lag Order Selection Criteria and Co-integration Analysis

VAR is selected due to several advantages over other statistical techniques. It describes the dynamic structure of the variables whereby all variables are treated *a priori* as endogenous. The structure is set up in a way that current variables may be explained by the lag of the variables involved. Hence, it is a good tool for forecasting or prediction. It is noted that there is only one variable integrated in levels or I(0), while other variables are integrated in order one or I(1). Therefore, every linear combination will likely result in series in I(1) or as non-stationary series. This is because the behaviour of non-stationary series tends to dominate the behaviour of stationary series.

As mentioned in Section 5.1, the macroeconomic variables are non-stationary in nature, except inflation rate as represented by CPI. As stated by Engle and Granger (1987), there is a possibility that the combination of two or more non-stationary series may co-integrate in the long-run – also known as the long-run equilibrium. Therefore, in order to investigate whether a relationship of co-integration exists among the variables, all variables are tested with the Johansen system co-integration test using EViews 8. However, prior to the test of co-integration, it is crucial to exercise a common procedure in choosing the optimal lag length; this procedure involves estimating the VAR model that includes all variables in levels. The selection of lags is automatically done by EViews 8 where the minimum value of selection criterion is determined. The result is shown in Table 5.6; minimum values are marked with asterisks denoting significance at the 5% level.

With reference to Lutkepohl (2005), each criterion has its own advantage. The researcher notes that FPE is a good tool for forecasting when the series are stationary, and the process is stable. The AIC and FPE criteria are asymptotically equivalent in a finite sample. However, the HQ and SC criteria prove to be consistent, as they have the ability to choose the correct order for a large sample. LR, on the other hand, is often misleading since its empirical distribution often does not comply with standard χ^2. In Table 5.6, LR and AIC suggested a lag of 12, while FPE suggested a lag of 2 instead. SC and HQ proved their consistency in establishing the lag's significance. Both suggested lag 1 as the optimal lag for VAR and co-integration tests, having the least values of SC and HQ.

Table 5.6 VAR Lag Order Selection Criteria for BLR, CPI, IPI, EER, M3, and VKLCI

Lag	LR	FPE	AIC	SC	HQ
0	NA	1.79E+11	45.777	45.922	45.836
1	2274.615	19310.35	29.733	30.887**	30.202**
2	96.546	18124.82**	29.665	31.830	30.545
3	67.211	20873.82	29.795	32.971	31.085
4	57.458	25574.88	29.975	34.162	31.677
5	75.032	26157.53	29.961	35.158	32.073
6	67.497	27993.92	29.974	36.181	32.496
7	56.205	32920.36	30.056	37.274	32.989
8	61.361	35824.13	30.031	38.260	33.375
9	53.139	42148.19	30.048	39.287	33.802
10	46.855	53091.26	30.086	40.336	34.251
11	77.498	41583.94	29.593	40.853	34.168
12	73.967**	32335.2	29.019**	41.291	34.006

Note: ** denotes lag order selected by the criterion at 5% significance level. LR, FPE, AIC, SC, and HQ denote the sequential modified LR test statistic, final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion respectively.

Therefore, lag 1, determined by SC and HQ criteria, is selected for further analyses in this section. The appropriate model is selected with regard to the deterministic components in the multivariate system. An important aspect in the formulation of the dynamic model is to determine whether intercept and/or a trend should enter the short-run model or the long-run model, or both. Results from the Johansen co-integration test in Table 5.7 justify that there is a long-term equilibrium among all variables, which are therefore co-integrated in the long-run. The table summarises results from the five models of the Johansen test for co-integration. The results are given in the trace statistic and maximum eigenvalue, as shown in the table.

Table 5.7 Number of Co-integrating Relations by Models

	Model 1		Model 2		Model 3		Model 4		Model 5	
Hypothesis	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**
r = 0	62.656**	165.89**	73.74**	204.93**	73.10**	149.82**	80.23**	169.69**	80.2**	167.18**
r ≤ 1	52.74**	103.23**	59.83**	131.19**	43.32**	75.72**	44.45**	89.45**	44.45**	86.98**
r ≤ 2	30.89**	50.49**	41.61**	71.35**	21.22	32.49	22.58**	44.99	21.73	42.52
r ≤ 3	14.87	19.6	21.14	29.75**	6.27	11.27	12.37	22.4	11.38	2.79

Note: ** denotes 5% critical values for the indicator of co-integrating equation based on the MacKinnon-Haug-Michelis (1999) test.

As illustrated in Table 5.7, three models hold consistency of two co-integrating equations as suggested by trace statistic and maximum eigenvalue. The three models are model 3, model 4, and model 5. Since three out of the five models are consistent in giving the number of co-integrating equation, the vector error equation model (VECM) is therefore estimated for two co-integrating equations.

Error Correction Model (ECM)

To recapitulate, this study tests four variables that are non-stationary and integrated at I(1). The Johansen test of co-integration suggests that all variables should be co-integrated, by definition, $\hat{u}_t \sim I(0)$. In other words, a linear combination of the variables at I(0) exists. Thus, the relationship between BLR, CPI, EER, IPI, M3, and VKLCI has the advantage of including both long-run and short-run information. The relationship may be expressed with an ECM specification:

$$\Delta Y_t = \alpha_0 + \beta_1 \Delta x_t - \pi \hat{u}_{t-1} + Y \quad (28)$$

The ECM model demonstrates that β_1 is the impact multiplier (the short-run effect) which measures the immediate impact x_t will have on any change in Y_t. π, on the other hand, is the feedback effect, or the adjustment effect, and shows the amount of disequilibrium being corrected:

$$\hat{u}_{t-1} = Y_{t-1} - \hat{\beta}_1 - \beta_2 x_{t-1} \quad (29)$$

From table 5.8, $\pi 1$ has an error coefficient of 0.988, which means that 0.98% of the adjustment takes place during each period. The coefficient is significant with a negative value, which is consistent with the assumption that $\gamma 1<1$, in order for the short-run model to converge on a long-run-solution. Results presented in Table 5.8 indicate that there is a long-run relationship of causality between BLR, CPI, EER, IPI, M3, and the volatility of KLCI. However, $\pi2$ has a positive 0.0143 value which means $\pi=(1-\alpha_1)$ is positive; and, because of the negative sign prefixing π, the overall effect is to push ΔY_t back towards its long path as determined by X_t in equation 28.

Table 5.8 Co-integrating Model (2000-2012) between BLR, CPI, EER, IPI, M3, and VKLCI

Variables	Coefficient	p(value)
$\pi1$	-0.988709	0
$\pi2$	0.01436	0
ΔBLR_{t-1}	-0.006959	0.1701
ΔCPI_{t-1}	0.00033	0.8588
ΔEER_{t-1}	0.052874	0.1415
ΔIPI_{t-1}	0.00284	0.702
$\Delta M3_{t-1}$	0.006507	0.8701
R^2	0.4703	
Adj R^2	0.441	
F-stat	16.90***	
Durbin-Watson	2.012	
Jarque-Bera	102.36	0
LM test	10.28	0.597
ARCH test	0.011	0.916

Note: *** denotes 1% level of significance.

In addition to the long-run equilibrium, the short-run relationship is also observed from the output in Table 5.8. The difference between CPI, EER, IPI, and M3 is positively related to the change in VKLCI, while change in BLR is negatively related to VKLCI. However, the relationships are not significant, as their p-values are above the 5% level of significance. Therefore, there is no significant short-run causal relationship between changes in BLR, CPI, EER, IPI, and M3 and any change in the volatility of the KLCI. These findings fail to reject hypothesis 1, which states that in the short-run, all macroeconomic variables do not significantly affect the volatility of KLCI.

In conclusion, about 47.03% of the variation in VKLCI is successfully explained by the regression, as indicated by the model's R^2. The model is also examined for normality, serial correlation, and presence of heteroscedasticity. The Durbin-Watson and LM tests consistently reject the null hypothesis that there is a serial correlation in the residuals. While the model is free of heteroscedasticity, the distribution of data is non-normal, as suggested by the Jarque-Bera test result. This is by far the best model fit that identifies the long-run relationship between the four macroeconomic variables and the volatility of KLCI measured from the year 2000-2012.

Autoregressive Distributive Lags

Consistent with other tests in examining the relationship between macroeconomic fundamentals and stock market volatility, the next analysis extracts results from the ARDL (p,q) bound testing model. In order to determine the appropriate model, it is tested with different lags. Table 5.9 summarises the analysis that contributes to the selection of a parsimonious ARDL (p,q) model.

Table 5.9 Summary of ARDL (p,q) Model with Designated Lags

Lags	AIC	SC	R^2	DW	AC
1	-9.34	-9.705*	0.215	2.32	Yes
2	-9.45	-9.058	0.329	2.14	Yes
3	-9.42	-8.938	0.384	2.1	No
4	-9.5	-8.904	0.483	1.93	No
5	-9.53*	-8.802	0.516	2.04	No
6	-9.47	-8.62	0.52	1.99	No
7	-9.5	-8.552	0.569	1.94	No
8	-9.45	-8.38	0.585	2.02	No
9	-9.42	-8.209	0.605	1.99	No
10	-9.39	-8.062	0.639	1.96	No
11	-9.37	-7.9	0.646	1.95	No
12	-9.27	-7.69	0.665	2.04	No

Note: * denotes the smallest AIC and SC criteria. DW denotes the Durbin-Watson test of autocorrelation. AC denotes autocorrelation tested by the LM test.

Table 5.9 demonstrates the criteria in selecting a parsimonious model to present the relationship between macroeconomic fundamentals and stock market volatility. As discussed in section 5.1, the SC criterion is selected because of its consistency (Lutkepohl, 2005). From the table, lag 1 is chosen due to its smallest SC criterion value. The other criterion to determine the best fit ARDL (p,q) is that the model should be free of autocorrelation. Therefore, from all model selection criteria, lag 1 seems to be the best fit model to observe the relationship.

Table 5.10 ARDL (1,1,1,1,1,1) Model (2000-2012) between BLR, CPI, EER, IPI, M3, and VKLCI

Variable	Coefficient	Std. Error	t-Statistic
C	0.1725	0.0398	4.3316
$VKLCI_{t-1}$	-0.88***	0.1139	-7.7303
BLR_{t-1}	0.0123***	0.0023	5.2374
CPI_{t-1}	0.00096	0.0012	0.7854
EER_{t-1}	-0.0368**	0.0147	-2.4961
IPI_{t-1}	-0.0131*	0.0067	-1.9527
$M3_{t-1}$	-0.013***	0.0034	-3.8472
$\Delta VKLCI_{t-1}$	0.0509	0.0877	0.5810
ΔBLR_{t}	-0.0003	0.0053	-0.0512
ΔBLR_{t-1}	0.0063	0.0053	1.1934
ΔCPI_{t}	-0.0018	0.0021	-0.8503
ΔCPI_{t-1}	0.0021	0.0022	0.9270
ΔEER_{t}	-0.0129	0.0415	-0.3114
ΔEER_{t-1}	0.0127	0.0396	0.3223
ΔIPI_{t}	-0.0115	0.0092	-1.2594
ΔIPI_{t-1}	-0.022**	0.0089	-2.5238
$\Delta M3_{t}$	-0.0098	0.0438	-0.2239
$\Delta M3_{t-1}$	0.0366	0.0440	0.8305

Note: ***, **, and * denote the significance level of 1%, 5%, and 10% respectively.

Table 5.10 shows the ARDL (1,1,1,1,1,1) model which examines long-run and short-run relationships between change in macroeconomic variables and change in KLCI volatility. Generally, several changes in macroeconomic variables maintain their significance to change in KLCI volatility. The model is represented in equation 30.

$$\Delta VKLCI_t = 0.1725 - 0.8803 VKLCI_{t-1} + 0.0123 BLR_{t-1} - 0.00001 CPI_{t-1} - 0.037 EER_{t-1} - 0.013 IPI_{t-1} \\ - 0.0132 M3_{t-1} + 0.051 \Delta VKLCI_{t-1} + 0.0002 \Delta BLR_t - 0.0063 \Delta BLR_{t-1} - 0.0018 \Delta CPI_t + 0.002 \Delta CPI_{t-1} \\ - 0.0129 \Delta EER_t - 0.0127 \Delta EER_{t-1} - 0.0115 \Delta IPI_t - 0.0225 \Delta IPI_{t-1} - 0.0098 \Delta M3_t - 0.036 \Delta M3_{t-1} + \mu_t \tag{30}$$

The first part of the equation in the ARDL model corresponds to a long-term relationship whereby the bound test for the null hypothesis of non-co-integration is tested using the ARDL (p,q) model. The long-run model is calculated in order to estimate long-run coefficients, and the calculated F-statistic is then compared to the critical value exhibited in Table 5.12, tabulated by Pesaran and Shin (1997). Regardless of whether the underlying integration orders of the variables are I(0) or I(1), the null hypothesis of no long-run relationship is rejected if the F-test statistic exceeds the upper critical value. Likewise, if the F-test statistic falls below the lower critical value, the null hypothesis will not be rejected. Nonetheless, the result will be inconclusive if the sample F-test statistic falls between these two bounds.

The hypothesis tested is the non-existence of a long-term relationship:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$$

Table 5.11 Wald Test: Coefficient Restriction

Test Statistic	Value
F-statistic	10.15

The excerpt of asymptotic critical value bounds for F-statistics suggested by Pesaran et al. (2001) is shown in Table 5.12. F-statistics for each of the bound analyses will then be computed and compared to critical values. In response to the results in Table 5.11, the coefficient test manifests an F-value of 10.15, which exceeds 2.62 and 3.79 at 5%

critical value on Panel III for k=5 variables. This even exceeds the 1% critical value for the upper bound. Therefore, the hypothesis of no long-run relationship is rejected.

Evidence therefore suggests the existence of a long-run relationship between the variables. On the other hand, the second part of equation 30 signifies a short-run relationship between macroeconomic fundamentals and KLCI. There is no evidence of a contemporaneous and near-term dynamic relationship with KLCI volatility (Table 5.10).

Table 5.12 Asymptotic Critical Value Bounds for the F-statistic of Testing for the Existence of Level Relationships

Panel I: No intercept and no trend

	0.1		0.05		0.025		0.01	
K	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
0	3	3	4.2	4.2	5.47	5.47	7.17	1.16
1	2.44	3.28	3.15	4.11	3.88	4.92	4.81	6.02
2	2.17	3.19	2.72	3.83	3.22	4.5	3.88	5.3
3	2.01	3.1	2.45	3.63	2.87	4.16	3.42	4.84
4	1.9	3.01	2.26	3.48	2.62	3.9	3.07	4.44
5	1.81	2.93	2.14	3.34	2.44	3.71	2.82	4.21
6	1.75	2.87	2.04	3.24	2.32	3.59	2.66	4.05
7	1.7	2.83	1.97	3.18	2.22	3.49	2.54	3.91
8	1.66	2.79	1.91	3.11	2.15	3.4	2.45	3.79
9	1.63	2.75	1.86	3.05	2.08	3.33	2.34	3.68
10	1.6	2.72	1.82	2.99	2.02	3.27	2.26	3.6

Panel III: Unrestricted intercept and no trend

	0.1		0.05		0.025		0.01	
K	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
0	6.58	6.58	8.21	8.21	9.8	9.8	11.79	11.79
1	4.04	4.78	4.94	5.73	5.77	6.68	6.84	7.84
2	3.17	4.14	3.79	4.85	4.41	5.52	5.15	6.36
3	2.72	3.77	3.23	4.35	3.69	4.89	4.29	5.61
4	2.45	3.52	2.86	4.01	3.25	4.49	3.74	5.06
5	2.26	3.35	2.62	3.79	2.96	4.18	3.41	4.68
6	2.12	3.23	2.45	3.61	2.75	3.99	3.15	4.43
7	2.03	3.13	2.32	3.5	2.6	3.84	2.96	4.26
8	1.95	3.06	2.22	3.39	2.48	3.7	2.79	4.1
9	1.88	2.99	2.14	3.3	2.37	3.6	2.65	3.97
10	1.83	2.94	2.06	3.24	2.28	3.5	2.54	3.86

Panel II: Restricted intercept and no trend

	0.1		0.05		0.025		0.01	
K	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
0	3.8	3.8	4.6	4.6	5.39	5.39	6.44	6.44
1	3.02	3.51	3.62	4.16	4.18	4.79	4.94	5.58
2	2.63	3.35	3.1	3.87	3.55	4.38	4.13	5
3	3.37	3.2	2.79	3.67	3.15	4.08	3.65	4.66
4	2.2	3.09	2.56	3.49	2.88	3.87	3.29	4.37
5	2.08	3	2.39	3.38	2.7	3.73	3.06	4.15
6	1.99	2.94	2.27	3.28	2.55	3.61	2.88	3.99
7	1.92	2.89	2.17	3.21	2.43	3.51	2.73	3.9
8	1.85	2.85	2.11	3.15	2.33	3.42	2.62	3.77
9	1.8	2.8	2.04	3.08	2.24	3.35	2.5	3.68
10	1.76	2.77	1.98	3.04	2.18	3.28	2.41	3.61

Panel IV: Unrestricted intercept and unrestricted trend

	0.1		0.05		0.025		0.01	
K	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
0	9.81	9.81	11.64	11.64	13.36	13.36	15.73	15.73
1	5.59	6.26	6.56	7.3	7.46	8.27	8.74	9.63
2	4.19	5.06	4.87	5.85	5.49	6.59	6.34	7.52
3	3.47	4.45	4.01	5.07	4.52	5.62	5.17	6.36
4	3.03	4.06	3.47	4.57	3.89	5.07	4.4	5.72
5	2.75	3.79	3.12	4.25	3.47	4.67	3.93	5.23
6	2.53	3.59	2.87	4	3.19	4.38	3.6	4.9
7	2.38	3.45	2.69	3.83	2.98	4.16	3.34	4.63
8	2.26	3.34	2.55	3.68	2.82	4.02	3.15	4.43
9	2.16	3.24	2.43	3.56	2.67	3.87	2.97	4.24
10	2.07	3.16	2.33	3.46	2.56	3.76	2.84	4.1

Note: I(0) and I(1) respectively represent the lower and upper bounds for each critical value.

In order to further analyse the magnitude of the long-run equilibrium, the coefficients need to be computed by estimating the following long-run ordinary least squares model (OLS) in levels as shown in Table 5.13:

$$VKLCI_t = \alpha_t + \beta_1 BLR_t + \beta_2 CPI_t + \beta_3 IPI_t + \beta_3 EER_t + \beta_4 M3_t + \mu_t \tag{31}$$

Table 5.13 Ordinary Least Squares Regression (2000-2012)

Variable	Coefficient	Std. Error	t-Statistic
C	0.184***	0.0320	5.7641
BLR_t	0.014***	0.0017	8.0829
CPI_t	0.0009	0.0010	0.8561
IPI_t	-0.011*	0.0059	-1.8970
EER_t	-0.037***	0.0130	-2.8113
$M3_t$	-0.016***	0.0028	-5.7600
R^2	0.379	D.W	1.76
AIC	-9.682		

Note: *** and * denote significance levels of 1% and 10% respectively.

Next, the restricted error correction term is fitted from the residual series constructed from equation 31.

Table 5.14 Long-run Equilibrium Model (2000-2012) with Restricted ECM

Variable	Coefficient	Std. Error	t-Statistic
C	0.0002	0.0003	0.6795
Z_{t-1}	-0.404***	0.0809	-5.0008
$\Delta VKLCI_{t-1}$	-0.1652**	0.0784	-2.1068
ΔBLR_t	-0.0005	0.0054	-0.0942
ΔBLR_{t-1}	-0.0014	0.0054	-0.2502
ΔCPI_t	-0.0020	0.0021	-0.9113
ΔCPI_{t-1}	0.0052**	0.0021	2.4397
ΔEER_t	0.0656	0.0408	1.6089
ΔEER_{t-1}	-0.0608	0.0398	-1.5275
ΔIPI_t	-0.0013	0.0093	-0.1442
ΔIPI_{t-1}	-0.0005	0.0091	-0.0587
$\Delta M3_t$	0.093**	0.0434	2.1648
$\Delta M3_{t-1}$	-0.159***	0.0458	-3.4828
R^2	0.394	DW	2.08
AIC	-9.586	LM Test	14.18
SC	-9.326	ARCH Test	0.009

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.

With reference to Table 5.14, Z_{t-1}, which is the error term in the model, indicates the price of adjustment reversed to long-run equilibrium following a short-run shock. Apparently, the coefficient of the error correction term, Z_{t-1}, is negative and highly significant. This is what one would have expected in case of co-integration between macroeconomic variables and KLCI volatility. The magnitude of this coefficient implies that 0.4% of any disequilibrium between macroeconomic variables and KLCI volatility is corrected within one-month. In the short-run, the one-month lag of inflation rate and money supply rate are able to predict significant change in KLCI volatility. The relationships between inflation rate and KLCI volatility are positive. On the other hand, the rate of broad money supply is negatively related to the KLCI volatility. This finding is consistent with a recent comparative study by Humpe and Macmillan (2009) in the context of Japan.

The next section discusses whether the predictive value of macroeconomic variables maintains its significance during the 2008 global financial crisis. However, prior to that, it is crucial to determine the appropriate structural break that coincides with the 2008 global financial crisis. As mentioned in detail in Chapter Four, the procedure suggested by Bai-Perron is adopted to detect significant structural breaks for the whole period of study. The results therefore support hypothesis 1(i), that inflation rate and money supply growth rate have significant causal relationship with the KLCI volatility. This also answers the first research question for the period of study (2000-2012). The result is, however, inconsistent with Zakaria and Shamsuddin (2012), who modelled KLCI volatility with GARCH (1,1) and found that only interest rate predicted KLCI volatility.

Structural Breaks in VKLCI

Before modelling the causal or predictive relationships between explanatory variables and KLCI volatility during the period of the global financial crisis, KLCI volatility is tested for structural breaks in order to identify episodes of unusual volatility due to the 2008 crisis. This helps achieve objectives 1(ii) and 2(ii) of this study, which are to observe differences of relationships between variables during that episode. Hence, the results following this section exhibit the relationship between the whole period of study and the effect of the global crisis. As suggested by Bai-Perron’s multiple breaks test in Table 5.15, the phase that coincides with the global crisis is identified as the period from January 2007 to February 2010. This is a period of 38 months; and, according to a common rule of thumb in statistics, a minimum of 30 observations is sufficient to carry out analysis (Hog and Tanis, 2005). Since the residuals of the VKLCI are serially uncorrelated, optimal trimming is selected at ϵ=0.15, where the maximum break is set at 5. The result is shown in Table 5.15:

Table 5.15 Structural Breaks Determined (2000-2012) by Bai-Perron’s Multiple Breaks Test

Breaks	**Coefficient**	**Std. Error**	**t-Statistic**
2000M04 - 2002M01	0.007***	0.00022	32.92477
2002M02 - 2004M07	0.004***	0.000234	17.69586
2004M08 - 2006M12	0.003***	0.000165	15.81902
2007M01 - 2010M02	0.006***	0.000307	18.42219
2010M03 - 2012M12	0.0029***	0.000364	8.077677
R-squared	0.485513	Mean dependent var	0.004409
Adjusted R-squared	0.471608	S.D. dependent var	0.002341
S.E. of regression	0.001702	Akaike info criterion	-9.882037
Sum squared resid	0.000429	Schwarz criterion	-9.783003
Log likelihood	760.9758	Hannan-Quinn crit	-9.841807
F-statistic	34.91632	Durbin-Watson stat	1.994798
Prob (F-statistic)	0		

Note: *** denotes the significance level of 1%.

Table 5.15 indicates five significant structural breaks from 2000-2012. The breaks are consistent with the number of stock market crashes and financial crises that took place during this period. The crises include the dot-com bubble that burst in the year 2001, which saw the collapse of many internet-based companies in the U.S and Malaysia. In addition to the dot-com crisis, the September 11 attacks in the United States worsened the situation. Another structural break where higher volatilities are observed was during the 2008 global financial crisis, originating in the United States. In accordance with Bai-Perron's structural test, the significant period was from January 2007 to February 2010, lasting 38 months. For a clearer view, the multiple breaks are charted in Figure 5.7, where five phases are identified throughout the period of study.

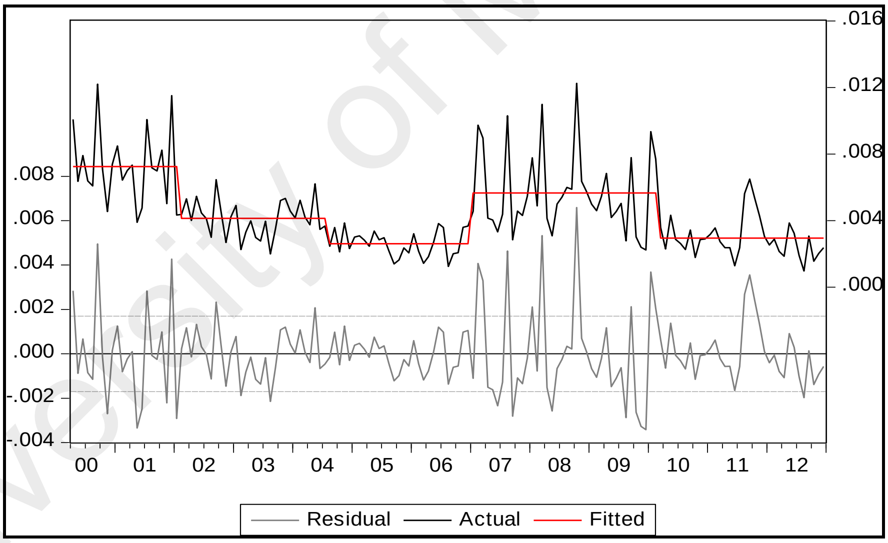


Figure 5.7 Structural Breaks for the Period of 2000-2012

5.3.2 The Global Financial Crisis [RQ1(ii)]

Since the variables comprise of different order integration, the appropriate model to examine the relationship between macroeconomic fundamentals and the volatility of the stock market is the ARDL (p,q) model. This model has been introduced in the earlier section of this chapter. Thus, in order to maintain consistency, the testing of most hypotheses in this study involve the application of ARDL (p,q) models throughout this chapter. Table 5.16 shows the relationship between the variables modelled by ARDL (1,1,1,1,1,1). The statistical hypothesis tested is:

H1(ii): Macroeconomic fundamentals (BLR, CPI, IPI, M3, EER) have no significant causal relationship with the volatility of KLCI for the period of the 2008 global financial crisis.

Table 5.16 ARDL (1,1,1,1,1,1) Model (2008 Global Financial Crisis) between BLR, CPI, EER, IPI, M3, and the VKLCI

Variable	Coefficient	Std. Error	t-Statistic
C	-0.274	0.4113	-0.6660
$VKLCI_{t-1}$	-3.838**	1.2972	-2.9586
BLR_{t-1}	0.018	0.0414	0.4311
CPI_{t-1}	0.006	0.0037	1.7004
EER_{t-1}	0.002	0.1261	0.0197
IPI_{t-1}	0.037	0.0550	0.6760
$M3_{t-1}$	0.033	0.0383	0.8606
$\Delta VKLCI_{t-1}$	2.297*	1.0747	2.1374
$\Delta VKLCI_{t-2}$	1.709*	0.8416	2.0316
$\Delta VKLCI_{t-3}$	1.0736	0.6413	1.6742
$\Delta VKLCI_{t-4}$	0.5361	0.4685	1.1443
$\Delta VKLCI_{t-5}$	0.2421	0.2783	0.8699
ΔBLR_{t-1}	0.0070	0.0968	0.0723
ΔCPI_{t-1}	-0.0009	0.0046	-0.2004
ΔEER_{t-1}	0.0600	0.1657	0.3617
$\Delta LIPI_{t-1}$	-0.0263	0.0411	-0.6393
$\Delta M3_{t-1}$	-0.0273	0.1296	-0.2108
R^2	0.757605	D.W	2.06
AIC	-8.771557	LM Test	3.043
SC	-7.985177	ARCH Test	0.467

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.

Generally, Table 5.16 indicates that none of the independent variables possess either long-term or short-term significant relationships with KLCI volatility. Nevertheless, for confirmation, the ARDL bound test is applied to observe if the coefficients of BLR_{t-1},

CPI_{t-1}, EER_{t-1}, IPI_{t-1}, and $M3_{t-1}$ are zero in our estimated model $H_0 = \gamma_1 = \gamma_2 = \gamma_3 = \lambda_4 = 0$.

The Wald test is employed to calculate an F-statistic of 2.61, which is then compared to the bound test in Table 5.12, with *k=5*. Since the calculated F-statistic falls between the lower and upper bounds of the 10% significance level, the test is inconclusive as to the existence of co-integrating relationships between the variables (Pesaran et al., 2001). This result concludes that macroeconomic fundamentals fail to prove their significance in predicting the movement of stock market volatility, specifically during the 2008 global financial crisis. When tested for autocorrelation and heteroscedasticity, the model is free from the influences of both. In extension to the ARDL (1,1,1,1,1,1) model yielding inconclusive evidence of a long-term equilibrium between the variables, the model is re-estimated to fit a restricted ECM. The result is displayed in Table 5.17.

Table 5.17 Multiple Regression Model (2008 Global Financial Crisis) between BLR, CPI, EER, IPI, M3, and VKLCI

Variable	Coefficient	Std. Error	t-Statistic
C	0.0003	0.000511	0.6695
Z_{t-1}	-1.333***	0.326727	-4.0784
$\Delta VKLCI_{t-1}$	0.2372	0.198699	1.1936
ΔBLR_{t-1}	0.0017	0.009479	0.18126
ΔCPI_{t-1}	0.0021	0.002955	0.71366
ΔEER_{t-1}	-0.0052	0.106298	-0.0485
$\Delta LIPI_{t-1}$	-0.0298	0.02245	-1.3287
$\Delta M3_{t-1}$	-0.1118	0.086195	-1.2965
R^2	0.641	D.W	2.09
AIC	-9.077	LM Test	1.692
SC	-8.722	ARCH Test	0.826

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.

It is noticeable that the coefficient of the error correction term, Z_{t-1}, is negative and significant at the 1% level. The magnitude of this coefficient implies that 1.33% of any disequilibrium between EUR and US is corrected within one period (one-month). This finding is consistent with results tabulated in Table 5.16. Nevertheless, the final model is free of the autocorrelation and ARCH effects, as shown by the LM and ARCH tests whereby the hypotheses of no serial correlation and heteroscedasticity respectively are not rejected. Results in Table 5.17 further confirm findings from the relationship modelled by ARDL (1,1,1,1,1,6) that none of the macroeconomic variables have significant predictive value regarding KLCI volatility. Therefore, hypothesis 1(ii) is rejected, concluding that macroeconomic fundamentals (BLR, CPI, IPI, M3, and EER) have no significant causal relationship with the volatility of KLCI during the global financial crisis.

The next section attempts to trace determinants of volatility with regards to the involvement of non-fundamental factors – in this case, the determinant of investor sentiment is proposed. Section 5.4 commences with the measurement of investor sentiment. Since there is no unanimous measure, this section suggests proxies that have been adopted and mentioned in research literature as possible measures of investor sentiment, particularly in the context of the Malaysian stock market.

5.4 Construction of Raw Investor Sentiment Composite Index (ISCI)

All proxies are tested individually prior to pooling them into a composite index using factor analysis. As discussed in Chapter 3, the proxies are extracted from various sources, including the stock market turnover (TURN), number of IPOs (NIPO), initial returns of IPOs (RIPO), advance/decline ratios (ADV), as well as the consumer sentiment index (CSI).

The initial stage is to analyse the proxies descriptively as shown in Table 5.18. To simplify interpretation, the data are transformed into logged variables prior to factor analysis. The results are used to compare the effectiveness of each variable to represent investor sentiment. Apart from the mean, median, minimum, and maximum values of the variables, the most important part is to determine the normality of data distribution. As is evident in Table 5.18, and consistent with results of the Jarque-Bera test, all variables are distributed non-normally. The p-values are significant at the 1% level, resulting in the rejection of the null hypothesis. Only the log-transformed NIPO is significant at the 5% level. NIPO has zero minimum values, while negative minimum values are observed on RIPO.

The results of the unit root test encompass the augmented Dickey-Fuller test with maximum lags of 13, and the Phillips-Perron test with automatic Newey-West bandwidth selection. The raw data show better results on unit root analysis, where four out of five variables have stationary residuals. From the ADF and PP tests on unit root test, NIPO, RIPO, ADV, and CSI have stationary residuals. Nevertheless, following log-transformation of the CSI series, the stationary of residuals seems to have been removed successfully. Accordingly, in order to maintain the originality of data, the next analysis will use raw data of all six variables as much as possible. The variables are TURN, NIPO, IPO, ADV, CSI, and VKLCI.

Table 5.18 Descriptive Statistics of Proxies

	RAW SERIES					LOG-TRANSFORMED SERIES				
	TURN	**NIPO**	**RIPO**	**ADV**	**CSI**	**TURN**	**NIPO**	**RIPO**	**ADV**	**CSI**
Mean	9223	2.993	0.231	1.296	108.402	3.366	0.498	0.063	0.080	0.520
Median	1583	2.000	0.084	1.146	110.647	3.200	0.477	0.033	0.057	0.505
Maximum	86689	13.000	2.723	3.330	126.000	4.881	1.146	0.571	0.523	0.689
Minimum	345.315	0	-0.671	0.5092	69.71778	2.467	0.000	-0.483	-0.293	0.392
Std. Dev.	19383	2.672	0.464	0.526	11.368	0.625	0.313	0.142	0.151	0.074
Skewness	2.436	1.107	2.351	1.488	-1.529	1.288	-0.233	0.196	0.632	0.987
Kurtosis	7.864	4.137	11.958	4.925	5.521	3.665	2.120	5.671	3.073	3.297
Jarque-Bera	308.093***	40.303***	665.408***	81.695***	102.147***	46.011***	6.449**	47.367***	10.404***	25.876***
Observations	156	156	156	156	156	156	156	156	156	156
ADF:										
with drift	-1.293	-3.457***	-11.736***	-5.62***	-5.243***	-1.311	-1.179**	-11.61***	-5.27***	-1.444
with drift and trend	-2.095	-4.135***	-12.211***	-9.483***	-5.162***	-2.625	-3.91***	-12.39***	-10.01***	-2.787
without drift and trend	-0.92	-1.928**	-3.677***	1.156	-0.15	0.219	-1.523	-3.558***	-4.44***	0.2009
PP:										
with drift	-2.092	-8.392***	-11.96***	-8.84***	-2.828**	-1.311	9.489***	-12.21***	-9.828***	-1.444
with drift and trend	-3.103	-8.97***	-12.29***	-9.574***	-2.757	-2.635	-10.286***	-12.68***	-10.314***	-2.842
without drift and trend	-1.1673	-4.367***	-10.81***	-2.576***	-0.238	0.252	-3.203***	-11.25***	-8.774***	0.204

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.
TURN represents stock market turnover, NIPO represents number of IPOs, RIPO represents initial return of IPOs, ADV represents advance/decline stocks, and CSI represents the consumer sentiment index published by MIER.

The next analysis observes the steps that lead to the construction of the investor sentiment composite index. This section of the analysis examines whether:

The proxy for stock market liquidity, the proxies for initial public offerings, the advancers/decliners ratio, and the consumer sentiment index published by MIER are appropriate measures of investor sentiment in the Malaysian stock market.

The objective particularly seeks to test the robustness of each variable as the appropriate proxy for investor sentiment. In doing so, each of the independent variables is tested against the dependent variable to detect any significant relationships which include the predictive value of independent variables. The tests include observation of correlation between the independent variables, and the study of causal relationships. The Spearman non-parametric test of correlation is chosen due to its simplicity; it does not limit data to the assumptions of the central-limit theorem.

Statistically, the hypothesis is tested based on correlations of the proxies to KLCI volatility. Results of the correlation are illustrated in Column 7 of Table 5.19, where TURN and ADV apparently possess strong correlations with the volatility of KLCI at the 1% level of significance. However, TURN has a negative correlation with the volatility of KLCI. NIPO also has a significant correlation with the volatility of KLCI. Nevertheless, as with TURN, the relationship is inverse in nature. The other proxy with a negative and insignificant relationship is RIPO, while CSI moves directly with the movement of KLCI volatility.

Table 5.19 Correlation between the Proxies

	$TURN_t$	**$NIPO_t$**	**$RIPO_t$**	**ADV_t**	**CSI_t**	**$VKLCI_t$**
$TURN_t$	1.000	-.159**	0.131	0.088	0.168**	-.341***
$NIPO_t$	-.159**	1.000	0.433***	-0.054	0.185**	-0.172**
$RIPO_t$	0.132	0.433***	1.000	0.173**	0.252***	-0.029
ADV_t	0.088	-0.054	0.173***	1.000	-0.058	0.396***
CSI_t	0.168**	0.185**	0.252***	-0.058	1.000	0.015
$VKLCI_t$	-0.341**	-.172**	-0.029	0.396***	0.015	1.000

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.

Apart from correlations with KLCI volatility, it is also noteworthy to observe correlations among the proxies. Column 2 demonstrates the correlation between $TURN_t$ and other proxies for investor sentiment. It is inversely correlated with $NIPO_t$, but adversely correlated with $RIPO_t$, ADV_t, and CSI_t. In column 3, $NIPO_t$ is positively correlated with $RIPO_t$ and CSI_t, and the relationship is significant at 5%. $NIPO_t$, however, is negatively correlated with $TURN_t$. The most interesting part is that the relationship between all the other proxies and CSI_t. $TURN_t$, $NIPO_t$, $RIPO_t$, and $VKLCI_t$ positively correlate with CSI, which leaves ADV and moves inversely with CSI. However, the relationship is insignificant. Before the construction of the investor sentiment composite index, an important step is to study the causal relationship between each variable and KLCI volatility. The relationship is critical as correlation analysis does not observe causal relationships among variables.

This method tests the following statistical hypothesis:

H2a-H2e: TURN, NIPO, RIPO, ADV, or CSI have no significant causal relationship with VKLCI

The vector autoregressive (VAR) model has several advantages over the standard ordinary least squares regression (OLS). One of the advantages is the simplicity of its structure and its effectiveness in forecasting. Nevertheless, it is important to examine the co-integrating relationship of the proxies and volatility of the KLCI because the variables are integrated in different order. Table 5.20 establishes the lag order selection determined by LR, FPE, AIC, SC, and HQ test statistics. However, preference is given to the lags that are consistently suggested by these criteria. Hence, results from FPE and AIC suggest lag 4 as appropriate to include in VAR and VECM modelling.

Table 5.20 VKLCI, TURN, NIPO, RIPO, ADV, and CSI Lag Order Selection Criteria

Lag	LR	FPE	AIC	SC	HQ
0	NA	41789.080	27.668	27.791	27.718
1	658.748	562.545	23.359	24.22**	23.711
2	161.446	271.120	22.627	24.236	23.281
3	152.560	132.742	21.906	24.257	22.86**
4	81.427	111.74**	21.72**	24.816	22.979
5	40.986	130.740	21.859	25.695	23.418
6	53.93*	134.130	21.855	26.434	23.716
7	32.810	166.646	22.031	27.351	24.193
8	36.303	198.481	22.148	28.212	24.612
9	47.851	206.060	22.111	28.917	24.876
10	37.359	238.667	22.161	29.709	25.228
11	48.466	237.210	22.031	30.322	25.400
12	48.266	231.397	21.851	30.885	25.522

Note: * and **denote lag order selected by the criteria at 5% significance level. LR, FPE, AIC, SC, and HQ denote the sequential modified LR test statistic, final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion respectively.

A further test of co-integrating relationships is applied using the Johansen test, and results are shown in Table 5.21. It is demonstrated that all five models are inconsistent in suggesting the number of co-integrating relationships between the variables. Due to absence of relationships, maximum eigenvalues and trace statistics suggest 2 co-integrating relationships from the Johansen co-integration test.

Table 5.21 Number of Co-integrating Relations by Model

	Model 1		Model 2		Model 3		Model 4		Model 5	
Hypothesis	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**	**Trace**
r=0	36.57**	92.1**	38.14	103.55	38.08	102.34**	50.33**	134.82**	50.07	133.55*
r≤1	31.07**	55.53	31.36	65.41	31.15	64.26	32.76	84.49	32.64	83.48**
r≤2	14.08	24.46	14.49**	34.05	14.46	31.11	27.87	51.73	27.86	50.86
Number of CE	1	0	0	0	0	1	1	1	1	2

Note: ** denotes 5% critical values for the indicator of co-integrating equation based on the MacKinnon-Haug-Michelis (1999) test.

The results may also lead to the conclusion that the variables are somehow not co-integrated (Asteriou and Hall, 2007). Nevertheless, in order to ensure that a possible co-integrating relationship based on Table 5.21, the estimation of error correction model (ECM) eventually leads to the co-integrating model as shown in Table 5.22.

Table 5.22 Multiple Regression Model between TURN, NIPO, RIPO, ADV, CSI, and VKLCI

X_{t-i}	Coefficient	t-Statistic
Z_{t-1}	-0.1528	-1.632
$\Delta TURN_{t-1}$	-0.000000003	-0.155
$\Delta TURN_{t-2}$	-0.00000002	-0.975
$\Delta TURN_{t-3}$	-0.00000002	-0.811
$\Delta TURN_{t-4}$	-0.00000003	-1.241
$\Delta NIPO_{t-1}$	0.00007	0.915
$\Delta NIPO_{t-2}$	0.00004	0.486
$\Delta NIPO_{t-3}$	-0.00002	-0.248
$\Delta NIPO_{t-4}$	-0.00008	-1.082
$\Delta RIPO_{t-1}$	0.00013	0.311
$\Delta RIPO_{t-2}$	0.0001	0.108
$\Delta RIPO_{t-3}$	-0.00041	-0.782
$\Delta RIPO_{t-4}$	-0.0007*	-1.775
ΔADV_{t-1}	-0.001**	-1.950
ΔADV_{t-2}	-0.0009	-1.546
ΔADV_{t-3}	-0.0012***	-2.467
ΔADV_{t-4}	-0.0005	-1.222
ΔCSI_{t-1}	0.0001	1.253
ΔCSI_{t-2}	-0.0002	-0.761
ΔCSI_{t-3}	0.00005	0.249
ΔCSI_{t-4}	-0.00008	-0.676
R^2	0.467	
Adj R^2	0.36	
F-stat	4.381***	
Durbin-Watson	1.979	
Jarque-Bera	31.91***	
LM test	5.067	
ARCH	12.703	

Note: ***, **, and * denote the significance level of 1%, 5%, and 10% respectively.

Regrettably, the equilibrium model as illustrated in Table 5.22 suffers from non-normality in the data distribution, with the presence of heteroscedasticity as justified by the Jarque-Bera statistic (χ^2=31.91) and the ARCH test (TR^2=12.703).

Due to the lack of a long-run relationship manifested by the insignificant value of Z_{t-1} (π = -0.1528), this is apparently not the best model. Therefore, further analysis is carried out to test the significance of a short-run relationship between the proxies and the volatility of KLCI. The Wald test coefficient diagnostic examines the hypothesis that the coefficients of the 4 lagged values of TURN, NIPO, RIPO, ADV, and CSI are zero in the volatility of the KLCI equation. The Wald test hypothesises that $H_0 = \gamma_1 = \gamma_2 = \gamma_3 = \lambda_4 = 0$. The Wald test statistics are asymptotically chi-square distributed with *p* degree of freedom. The test result is shown in Table 5.23.

Table 5.23 Wald Coefficient Diagnostic Test Results

Proxies	χ^2	**P (value)**
TURN	2.167	0.7051
NIPO	2.394	0.6637
RIPO	5.149	0.2723
ADV	7.833*	0.0979
CSI	7.343	0.1188

Note: * denotes the 10% level of significance.

As illustrated in Table 5.23, only ADV has a significant chi-square (χ^2) value, which means that the combined lags of advance/decline stocks ratios possess a short-run causal relationship with the volatility of KLCI. The analyses conclude that TURN, NIPO, RIPO, and CSI have neither long-run nor short-run relationships with VKLCI. Overall, each proxy was tested with regard to its relationship and its predictive ability regarding the volatility of KLCI. The results from Table 5.19 show that TURN, NIPO, and RIPO independently possess a negative correlation with the volatility of KLCI, while ADV and CSI correlate positively with the volatility of KLCI.

These findings fail to reject hypotheses 2(a), 2(b), 2(c), and 2(e); therefore, it may be concluded that TURN, NIPO, RIPO, and CSI have no significant causal relationship with the volatility of KLCI. Nevertheless, the results also show that only ADV has a significant causal relationship with the volatility of KLCI at the 10% acceptance level, thus leading to the rejection of hypothesis 2(d). With reference to the robustness test, the relationship of variables as a group – which is expected to have common underlying factors from proxies – is observed. Hence, this study employs factor analysis in order to study the patterns of relationship among the dependent variables. The purpose of this method is to discover the nature of all independent proxies that affect their behaviour as a common factor. Therefore, to meet the second research objective, a single index that may represent the investor sentiment of Kuala Lumpur stock market is constructed by adopting factor analysis with Principal Component Analysis (PCA) extraction.

In essence, the objective of factor analysis is to summarise the underlying factor contained in all proxies, and to consolidate the proxies into a single composite index. Factor analysis – a multivariate statistical technique – summarises the information underlying a large number of variables into a smaller set of factors. Consistent with Baker and Wurgler (2007), each of the proxies is tested in current and one-month lags. Following this, each proxy is tested to determine lead and lag relationships with the constructed composite index. Next, the correlation between each proxy and their respective lags is computed. The results are presented on Table 5.24.

Table 5.24 Correlation between Proxies and Lags

	$TURN_t$	$TURN_{t-1}$	$NIPO_t$	$NIPO_{t-1}$	$RIPO_t$	$RIPO_{t-1}$	ADV_t	ADV_{t-1}	CSI_t	CSI_{t-1}
$TURN_t$	1.000	0.912***	-0.278***	-0.283***	-0.063	-0.106*	-0.157**	-0.131**	0.129**	0.121*
$TURN_{t-1}$	0.912***	1.000	-0.269***	-0.269***	-0.018	-0.061	-0.176***	-0.154***	0.133**	0.12*
$NIPO_t$	-0.278***	-0.269***	1.000	0.462	0.261***	0.186***	-0.11*	0.014	0.225***	0.206***
$NIPO_{t-1}$	-0.283***	-0.268***	0.462***	1.000	0.148**	0.244***	-0.238***	-0.126**	0.248***	0.228***
$RIPO_t$	-0.063	-0.018	0.261***	0.148***	1.000	0.067	0.128**	0.274***	0.184***	0.232***
$RIPO_{t-1}$	-0.106*	-0.062	0.186***	0.245**	0.067	1.000	0.100	0.167***	0.149**	0.195***
ADV_t	-0.157**	-0.176***	-0.11*	-0.238***	0.128**	0.1*	1.000	0.403***	0.024	-.004
ADV_{t-1}	-0.131***	-0.154**	0.014	-0.126**	0.274***	0.167***	0.403***	1.000	0.066	.045
CSI_t	0.129**	0.133**	0.225***	0.248***	0.184***	0.149**	0.024	0.066	1.000	0.942***
CSI_{t-1}	0.121*	0.12*	0.206***	0.228***	0.232***	0.195***	-0.004	0.045	0.942***	1.000

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. $TURN_t$ and $TURN_{t-1}$ represent stock market turnover in current and one-month lag; $NIPO_t$ and $NIPO_{t-1}$ represent number of IPOs in current and one-month lags; $RIPO_t$ and $RIPO_{t-1}$ represent initial return of IPOs in current and one-month lags; ADV_t and ADV_{t-1} represent advance/decline stocks in current and one-month lags; CSI_t and CSI_{t-1} represent the consumer sentiment index published by MIER in current and one-month lags.

The correlations between proxies and their lags are shown in Table 5.24. $TURN_t$ shows significant correlations with all proxies except $RIPO_t$. $TURN_{t-1}$, on the other hand, has no significant correlations with $RIPO_t$ or $RIPO_{t-1}$. NIPO (current as well as one-month lags) demonstrates a strong significant correlation with all other proxies on the index. However, ADV_t and ADV_{t-1} have no significant correlation with CSI in current or one-month lags. It may be concluded that most proxies correlate significantly with each other, thus justifying the inclusion of TURN, RIPO, NIPO, ADV, and CSI in the investor sentiment composite index. The next section demonstrates further steps in the construction of the sentiment composite index with the use of principal component analysis.

5.4.1 Determination of Initial Factors Using Principal Component Analysis (PCA)

Initial factors are usually determined by factor analysis with PCA extraction based on total variation in the data. Consistent with Baker and Wurgler (2006), the first-stage index (FSI) is formed from variables and their designated lags. FSI is actually the first principal component (PC1) to be calculated from the weighted linear combination of variables; it accounts for the largest amount of total variation in the data. This means that FSI is the linear combination of the proxies:

$$FSI = W_1 TURN_t + W_2 TURN_{t-1} + W_3 NIPO_t + W_4 NIPO_{t-1} + W_5 RIPO_t + W_6 RIPO_{t-1} + W_7 ADV_t + W_8 ADV_{t-1} + W_9 CSI_t + W_{10} CSI_{t-1} \quad (32)$$

The weights (W) are chosen to maximise the quantity of variance. The variance obtained by each principal component is explained in Table 5.25, where PC1 has the highest percentage of variance (σ^2=25.28%), followed by PC2 and PC3.

Table 5.25 Total Variance Explained by Each Component

Components	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
PC1	2.529	25.286	25.286
PC2	2.230	22.297	47.583
PC3	1.634	16.336	63.920

The first principal component was adopted by Baker and Wurgler (2006) as the first-stage factor, which comprises of all variables and their respective lags. With reference to Baker and Wurgler (2006), Table 5.26 exhibits non-parametric Pearson's correlation between the proxies and the first-stage index. This step is taken to determine which timing is appropriate to represent the proxies in constructing the composite index. The proxies with significant FSI correlations are selected as timing effects. The correlation with FSI is shown in Column 12, where – according to each variable's significant value – TURN, RIPO, ADV, and CSI have lagging effect to the first-stage index, while NIPO has an immediate effect on the first-stage index. The timings of TURN, NIPO, and RIPO are therefore consistent with findings in Baker and Wurgler (2006; 2007; 2012). The effect of ADV and CSI on sentiment have not yet been tested in existing studies; therefore, a comparison cannot be made with findings from this study.

Table 5.26 Correlation between Proxies with Lags and FSI

	TURN$_t$	**TURN**$_{t-1}$	**NIPO**$_t$	**NIPO**$_{t-1}$	**RIPO**$_t$	**RIPO**$_{t-1}$	**ADV**$_t$	**ADV**$_{t-1}$	**CSI**$_t$	**CSI**$_{t-1}$	**FSI**$_t$
TURN$_t$	1.000	.912***	-.278***	-.283***	-0.063	-0.106	-0.157**	-0.131*	0.129*	0.121	0.106
TURN$_{t-1}$	.912***	1.000	-.269***	-.276***	-0.018	-0.066	0-.176**	-0.157**	0.133*	0.127	0.125*
NIPO$_t$	-0.278**	-0.269**	1.000	0.462**	0.261**	0.186*	-0.110	0.014	0.225**	0.206**	0.445***
NIPO$_{t-1}$	-0.283**	-0.276**	0.462**	1.000	0.1485*	0.247***	-.238***	-0.122	0.248***	0.220***	0.437***
RIPO$_t$	-0.063	-0.018	0.261***	0.148*	1.000	0.067	0.128	0.274***	0.184**	0.232***	0.432***
RIPO$_{t-1}$	-0.106	-0.066	0.186**	0.247**	0.067	1.000	0.100	0.168**	0.1487*	0.192***	0.362***
ADV$_t$	-0.157**	-0.176**	-0.110	-0.238***	0.128	0.100	1.000	0.403***	0.024	-0.004	-0.005
ADV$_{t-1}$	-0.131	-0.157**	0.014	-0.122	0.274***	0.168**	0.403**	1.000	0.066	0.042	0.145*
CSI$_t$	0.129*	0.133*	0.225***	0.248***	0.184**	0.149*	0.024	0.066	1.000	0.942***	0.903**
CSI$_{t-1}$	0.121	0.127	0.206***	0.220***	0.232***	0.192***	-0.004	0.042	0.942***	1.000	0.909***
FSI$_t$	0.106	0.124	0.445**	0.437**	0.432**	0.462**	-0.005	0.145*	0.903***	0.909**	1.000

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. TURN$_t$ and TURN$_{t-1}$ represent stock market turnover in current and one-month lag. NIPO$_t$ and NIPO$_{t-1}$ represent number of IPOs in current and one-month lags. RIPO$_t$ and RIPO$_{t-1}$ represent initial return of IPOs in current and one-month lags. ADV$_t$ and ADV$_{t-1}$ represent advance/decline stocks in current and one-month lags. CSI$_t$ and CSI$_{t-1}$ represent the consumer sentiment index published by MIER in current and one-month lags.

The next step is to run factor analysis with PCA extraction for the five proxies with their respective lags, in order to finalise the construction of the investor sentiment composite index. Table 5.27 exhibits the factor loadings which comprise of correlations for each proxy according to their respective factors.

Table 5.27 Factor Loadings for PC1, PC2, and PC3

	Principal Component		
	1	2	3
$TURN_{t-1}$	0.270	-0.821	-0.228
$NIPO_{t}$	0.427	0.756	-0.154
$RIPO_{t-1}$	0.571	0.138	0.449
ADV_{t-1}	0.010	0.029	0.911
CSI^{t-1}	0.842	-0.060	-0.046

It is observed that PC1 has the largest variance of the data; it is therefore defined as the investor sentiment composite index. Results from Table 5.27 show that CSI_{t-1} has the strongest correlation (ρ=0.842) with the investor sentiment composite index. The second highest correlation with the composite index is that of $RIPO_{t-1}$, followed by $NIPO_{t}$ (ρ=0.427), $TURN_{t-1}$ (ρ=0.27), and finally ADV_{t-1} which has a weak correlation at 0.01. All proxies enter the index with positive relationships. Therefore, any increase in $TURN_{t-1}$, $NIPO_{t}$, $RIPO_{t-1}$, ADV_{t-1}, or CSI_{t-1} increases the value of the composite index.

This is followed by computation of the factor score, which is a weighted linear combination of the original series similar to equation 32. The procedure leads to a parsimonious composite index:

$$ISCI = 0.28TURN_{t-1} + 0.29NIPO_{t} + 0.412RIPO_{t-1} + 0.049ADV_{t-1} + 0.669CSI_{t-1} \quad (33)$$

The factor score is the weighted sums of the original standardised series, making up for the composite index as displayed in Figure 5.8.

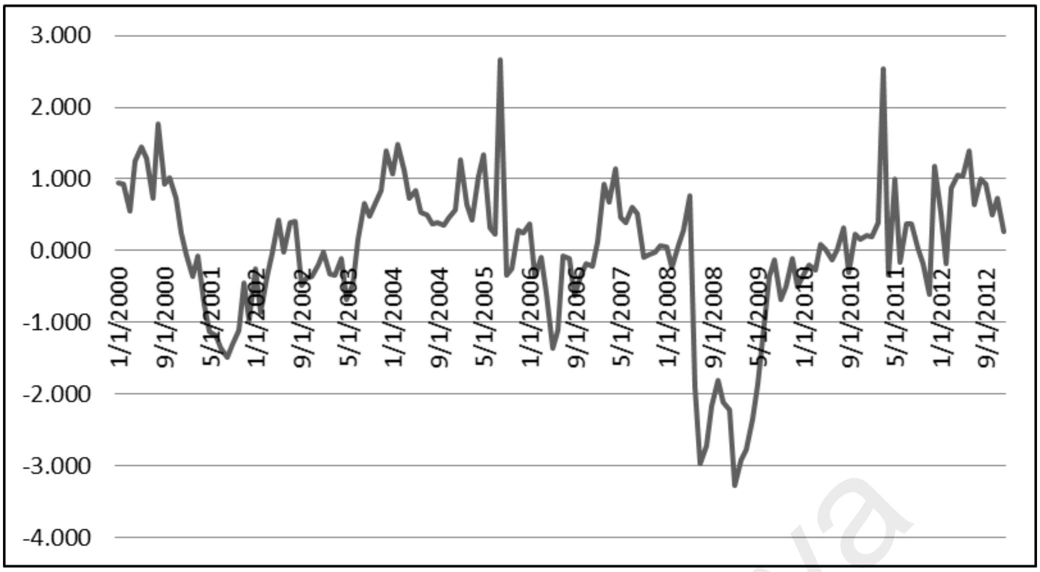


Figure 5.8 Movement of ISCI from 2000-2012

As shown in Figure 5.8, the investor sentiment composite index (ISCI) is constructed from raw data of five proxies made up of positive sentiments. Sentiment was at its highest in August 2005 (I*SCI*=2.67) and in March 2011 (I*SCI*=2.54). The apparent episode was during the global financial crisis during 2007-2008, when the ISCI was at its lowest point (I*SCI*=-3.28). This affected the Malaysian economy as well as other countries throughout the world. However, beginning in the middle of 2010, the pattern seems to have reversed to positive territory until the end of 2012.

As discussed in the methodology (Chapter Four), a critical measure in obtaining true investor sentiment representative consistent with its definition is constructed. The proxy must be free from the influence of macroeconomic fundamentals. Therefore, each proxy is regressed with macroeconomic variables in order to obtain a cleaner measure of investor sentiment as demonstrated by Baker and Wurgler (2006). As shown in Tables 5.1 and 5.18, the macroeconomic variables and proxies consist of data with residuals of different order integration. Therefore, as suggested by Pesaran and Shin (1997), the co-integration comprises of different order integration, and is measured by the ARDL bound test model. Since the objective of this section is to obtain a cleaner measure of investor sentiment composite index which is net macroeconomic fundamentals, the variables are regressed into a parsimonious model. The residuals, also known as noise factor from the model, are adopted as the cleaner index. Nevertheless, as most of the series suffer from non-stationarity of the residuals, the standard OLS and VAR are not suitable to model the relationship. The ARDL model with bound test is by far the closest parsimonious method to model the relationship between macroeconomic fundamentals and the proxies that comprise of variables with different integrated order.

5.5 Construction of Cleaner Index for Investor Sentiment ($ISCI^C$)

With reference to Baker and Wurgler (2006; 2007; 2012), in obtaining cleaner measures for the investor sentiment composite index, each proxy is regressed with macroeconomic fundamental variables, and then the residuals are taken for further analysis. Residuals are considered as cleaner proxies, since they are free from the influence of macroeconomic fundamentals. In doing so, the ARDL (p,q) model is adopted. The ARDL (p,q) model has a number of advantages over VAR or ECM. Firstly, it estimates the relationships in level. The model suggests that once the order of co-integration is recognised, the relationship can be estimated with the OLS standard. Secondly, it introduces the bound test that allows the mixture of I(0) and I(1) variables as regression. Thirdly, the approach involves a single equation set-up, which makes it easier to implement and interpret. Finally, different variables may be assigned with different lag lengths as they entered the model (Pesaran, Shin, and Smith, 2001). Thus, the adoption of ARDL (p,q) models can be observed throughout this chapter in testing various relationship hypotheses.

One of the initial steps to model ARDL (p,q) is the maximum selection of lags. Similar to VAR, lag selection is determined by suggestions from AIC and SC criteria. Nevertheless, as observed in previous analyses, SC is consistent and provides the least lag for the model. Table 5.28 shows the sequence of variables modelled by VAR and the lags suggested by AIC and SC criteria.

Table 5.28 Lag Selection by AIC and SC criteria for ARDL Models

Variables sequence	AIC	SC
TURN, BLR, CPI, EER, IPI, M3	49.374 (lag 12)	51.126 (lag1)
NIPO, BLR, CPI, EER, IPI, M3	33.312 (lag 12)	34.542 (lag1)
RIPO, BLR, CPI, EER, IPI, M3	30.394 (lag 12)	31.453 (lag 1)
ADV, BLR, CPI, EER, IPI, M3	29.933 (lag 12)	31.274 (lag 1)
CSI, BLR, CPI, EER, IPI, M3	31.961 (lag 12)	35.178 (lag 3)

The four VAR models suggest a maximum of one lag according to the SC criterion. The following models are suggested with one lag by the SC criterion:

TURN, BLR, CPI, EER, IPI, M3

NIPO, BLR, CPI, EER, IPI, M3

RIPO, BLR, CPI, EER, IPI, M3

ADV, BLR, CPI, EER, IPI, M3

For the CSI, BLR, CPI, EER, IPI, M3 model, the SC criterion suggests a maximum of lag 3. Equations 34-38 represent the ARDL (p,q) model for TURN, NIPO, RIPO, ADV and CSI for a maximum lag of three months, each suggested by the SC criterion.

The estimated ARDL model for TURN, NIPO, RIPO, ADV and CSI is as follows:

$$\Delta TURN_t = 0.006\Delta TURN_{t-1} + 0.014\Delta BLR_{t-1} - 0.203\Delta CPI_{t-1} - 2.396\Delta EER_{t-1} + 0.282\Delta IPI_{t-1} - 0.875\Delta M3_{t-1} - 0.12^{***}TURN_{t-1} - 0.368^{***}BLR_{t-1} + 0.025CPI_{t-1} + 2.551^{*}EER_{t-1} - 0.195IPI_{t-1} + 0.885M3_{t-1} + \varepsilon_t \quad (34)$$

$$\Delta NIPO_t = -0.178^{**}\Delta NIPO_{t-1} + 0.443\Delta BLR_{t-1} - 0.038\Delta CPI_{t-1} + 0.012\Delta EER_{t-1} + 0.322\Delta IPI_{t-1} - 7.849\Delta M3_{t-1} - 0.777^{***}TURN_{t-1} - 0.741^{***}BLR_{t-1} - 0.158CPI_{t-1} + 1.41EER_{t-1} + 1.956^{***}IPI_{t-1} - 0.541M3_{t-1} + \varepsilon_t \quad (35)$$

$$\Delta RIPO_t = -0.1372\Delta RIPO_{t-1} + 0.897^{**}\Delta BLR_{t-1} + 0.0887\Delta CPI_{t-1} - 0.8588\Delta EER_{t-1} + 0.1233\Delta IPI_{t-1} - 2.2769\Delta M3_{t-1} - 0.881^{***}TURN_{t-1} - 0.205^{***}BLR_{t-1} - 0.1033CPI_{t-1} + 1214EER_{t-1} + 0.0821IPI_{t-1} - 0.0235M3_{t-1} + \varepsilon_t \quad (36)$$

$$\Delta ADV_t = 0.1052\Delta ADV_{t-1} - 0.0854\Delta BLR_{t-1} - 0.0129\Delta CPI_{t-1} - 0.7469\Delta EER_{t-1} + 0.2584\Delta IPI_{t-1} + 1.4027\Delta M3_{t-1} - 1.014^{***}TURN_{t-1} + 0.444^{***}BLR_{t-1} - 0.0365CPI_{t-1} - 0.0542EER_{t-1} - 1.513^{***}IPI_{t-1} - 2.8^{**}M3_{t-1} + \varepsilon_t \quad (37)$$

$$\Delta CSI_t = 0.068\Delta CSI_{t-1} - 0.0149\Delta CSI_{t-2} + 0.144^{*}\Delta CSI_{t-3} + 0.013\Delta BLR_{t-1} + 0.043\Delta BLR_{t-2} + 0.088\Delta BLR_{t-3} - 0.03\Delta CPI_{t-1} - 0.019\Delta CPI_{t-2} - 0.0108\Delta CPI_{t-3} - 0.49\Delta EER_{t-1} + 0.1297\Delta EER_{t-2} - 0.915^{**}\Delta EER_{t-3} + 0.1924\Delta IPI_{t+1} + 0.1646\Delta IPI_{t+2} + 0.0573\Delta IPI_{t+3} - 0.2898\Delta M3_{t+1} + 0.925^{*}\Delta M3_{t+2} + 0.011\Delta M3_{t+3} - 0.165^{***}CSI_{t-1} - 0.056^{**}BLR_{t-1} + 0.012CPI_{t-1} + 0.342^{*}EER_{t-1} - 0.072IPI_{t-1} + 0.145M3_{t-1} + \varepsilon_t \quad (38)$$

With regards to short-run dynamics between the variables as shown by equations 34-38, only BLR has a dynamically significant effect on RIPO at the 5% level. BLR's one-month lag significantly predicts change in IPO's initial returns in the Malaysian stock market. Apart from RIPO, other variables have no significant short-run relationships as modelled by ARDL (p,q). On the other hand, the presence of a long-run relationship of the model can be determined by running a Wald analysis to test the hypothesis that joint hypotheses of all coefficients equal zero. Results from the F-statistic are then compared to Pesaran et al.'s (2001) asymptotic critical value bounds for the F-statistic. If the computed F-statistic from Wald test falls below the lower bound or I(0) as shown in Table 5.12, there is a possibility that there is no co-integrating relationship. However, if the F-statistic exceeds the upper bound, a co-integrating relationship is observed. Finally, if the F-statistic falls between the bounds, the test is considered inconclusive.

When an F-test of the hypothesis H_0: $\theta_0 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = 0$ is performed, the coefficient bound test is the conventional co-integration testing which examines the absence of a long-run equilibrium relationship between the variables. The absence coincides with zero coefficients for Y_{t-1}, X_{1t-1}, X_{2t-1} X_{3t-1} X_{4t-1}, X_{5t-1} from equation 42. A rejection of H_0 implies that there is a long-run relationship between the variables.

$$\Delta Yt = \beta_0 + \sum \beta_1 \Delta Y_{t-i} + \sum \gamma_j \Delta X1_{t-j} + \sum \delta_k \Delta X2_{t-k} + \sum \eta_{l\Delta_{t-l}} \Delta X3_{t-1} + \sum \nu_m X4_{t-m} + \sum \varpi_n \Delta X5_{t-n}$$
$$+ \theta_0 Y_{t-1} + \theta_1 X1_{t-1} + \theta_2 X2_{t-1} + \theta_3 X3_{t-1} + \theta_4 X4_{t-1} + \theta_5 X5_{t-1} + \varepsilon \qquad (39)$$

The computed F-statistics of each hypothesis are given in Table 5.29. In accordance with Pesaran et al. (2001), only two models from this study indicate the absence of long-run relationships between proxies and macroeconomic variables. The first of these is the model comprised of TURN, BLR, CPI, EER, IPI, M3 shown by equation 34, and the second is the model comprised of CSI, BLR, CPI, EER, IPI, M3 from equation 38.

Table 5.29 Bound Testing (Pesaran et al., 1997)

ΔY_t	Case	F-statistic	10%		5%		1%		Conclusion
			I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
$\Delta TURN_t$	No intercept, no trend	2.206	2.26	3.35	26.2	3.79	3.41	4.68	Not co-integrated
$\Delta NIPO_t$	No intercept, no trend	7.966	1.81	2.93	2.14	3.34	2.82	4.21	Co-integrated
$\Delta RIPO_t$	No intercept, no trend	9.52	1.81	2.93	2.14	3.34	2.82	4.21	Co-integrated
ΔADV_t	Intercept, trend	14.64	2.75	3.79	3.12	4.25	2.93	5.23	Co-integrated
ΔCSI_t	Intercept, no trend	2.91	1.81	3.35	2.62	3.79	3.41	4.68	Inconclusive

There are three models that evidently hold long-run relationships between the variables. These are model 2 represented by equation 35 (NIPO, BLR, CPI, IPI, EER, M3), model 3 represented by equation 36 (RIPO, BLR, CPI, IPI, EER, M3), and model 4 represented equation 37 (ADV, BLR, CPI, IPI, EER, M3). Nevertheless, the main purpose of running the variables through the ARDL (p,q) model is to obtain a cleaner measure for each proxy to represent a cleaner representative of the investor sentiment composite index, which results in an index free from the influence of macroeconomic fundamentals. Therefore, the final ARDL (p,q) models for each proxy free from autocorrelation and heteroscedasticity are as follows:

$$\Delta TURN_t = 9.445^{***} - 0.117^{***}TURN_{t-1} - 0.365^{**}BLR_{t-1} + 2.69^{**}EER_{t-1} + 0.803^{***}M3_{t-1} + \varepsilon$$
$$R^2 = 0.089;\ D.W = 2.004 \tag{40}$$

$$\Delta NIPO_t = -0.219^{***}\Delta NIPO_{t-1} - 0.669^{***}NIPO_{t-1} - 0.679^{***}BLR_{t-1} + 0.128^{***}M3_{t-1} + \varepsilon$$
$$R^2 = 0.464;\ D.W = 2.045 \tag{41}$$

$$\Delta RIPO_t = -0.151^{*}\Delta RIPO_{t-1} + 0.826^{**}\Delta BLR_{t-1} - 0.194^{***}BLR_{t-1} + 0.084^{***}EER_{t-1} + \varepsilon$$
$$R^2 = 0.526;\ D.W = 2.013 \tag{42}$$

$$\Delta ADV_t = 14.244^{**} - 0.872^{***}ADV_{t-1} + 0.36^{***}BLR_{t-1} - 1.33^{**}IPI_{t-1} + \varepsilon$$
$$R^2 = 0.469;\ D.W = 2.04 \tag{43}$$

$$\Delta CSI_t = -1.167 - 0.125^{***}CSI_{t-1} - 0.048^{**}BLR_{t-1} + 0.332^{**}EER_{t-1} + 0.102^{***}M3_{t-1} + \varepsilon$$
$$R^2 = 0.01;\ D.W = 1.92 \tag{44}$$

As a general interpretation, stock market turnover (TURN) is influenced by the base lending rate (BLR), the exchange rate (EER), and the circulation of broad money (M3). For instance, an increase in BLR negatively affects stock market turnover. In contrast, the exchange rate and broad money circulation have a positive impact on stock market turnover. A change in the number of IPOs (NIPO) is also influenced by the base lending rate (BLR) and circulation of broad money (M3). As with TURN, BLR has an inverse relationship and M3 has an adverse relationship with NIPO. Equation 42 represents the final RIPO model with macroeconomic fundamentals, where change in BLR has a considerable impact on change in IPO initial returns. Additionally, the exchange rate has a minimal positive effect on RIPO. A noteworthy relationship is the reverse result showed by advancer/decliner stocks with macroeconomic fundamentals. Inconsistent with other proxies, ADV shows a positive relationship with BLR and a significant inverse relationship with the industrial production index (IPI).

Finally, consistent with TURN, the consumer sentiment index (CSI) seems to be affected by the movement of BLR, EER, and M3. As with TURN, NIPO, and RIPO, an increase in BLR significantly affects declining change in CSI. The final models were tested for normality, serial correlation, and heteroscedasticity to meet the general assumptions of the ordinary least squares method. Results confirm that the models are also free from autocorrelation (according to the LM test) and heteroscedasticity (examined by the ARCH test). The next step is to extract residuals of the models in order to construct a cleaner measure for the investor sentiment composite index.

The residuals, also known as cleaner data, are furnished in Appendix D of this study. The construction of a cleaner investor sentiment index follows the same procedures as in the construction of the ISCI with raw proxies earlier on in this chapter. Each cleaner proxy incorporates a month lag and the current lag in order to construct the first-stage index (FSI). In order to determine the correct timing of each proxy that correlates to the cleaner index movement, their correlations with FSI are computed. From Table 5.30, each respective current proxy or one-month lag (whichever has a higher correlation with the first-stage index) is then selected for construction of the cleaner investor sentiment composite index.

Table 5. 30 Correlations between Current and One-month Lag Proxies with FSI

	$TURN^C_t$	$TURN^C_{t-1}$	$NIPO^C_t$	$NIPO^C_{t-1}$	$RIPO^C_t$	$RIPO^C_{t-1}$	ADV^C_t	ADV^C_{t-1}	CSI^C_t	CSI^C_{t-1}
FSI	0.153**	0.922***	0-.160**	-0.048	0.260***	0.136*	0.293***	0.067	0.166**	0.921***

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

The final selection of a cleaner timing of proxies includes: $TURN^{C}_{t-1}$, $NIPO^{C}_{t}$, $RIPO^{C}_{t}$, ADV^{C}_{t}, and CSI^{C}_{t-1}. Next, proxies with respective timings are applied to the factor analysis with PCA extraction. Each of the index components is standardised and coefficients are rescaled to a unit variance. Results from factor analysis with PCA extraction are rotated using Varimax (Table 5.31). Two principal components account for a cumulative 67% of the variance from the cleaner proxies (Table 5.31).

Table 5.31 Total Variance Explained by Each Component

Component	**Initial Eigenvalues**		
	Total	**% of Variance**	**Cumulative %**
PC1	2.153	43.065	43.065
PC2	1.198	23.953	67.018

As suggested by Baker and Wurgler (2006; 2007; 2012), PC1, being the first principal component that accounts for the largest variation (σ^2), is selected as the investor sentiment composite index. Factor loadings for PC1 and PC2 are shown in Table 5.32. Factor loadings justify the correlation of each cleaner proxy to each component, while factor weights represent how much each proxy contributes towards the constructed index. Factor weights are also used to calculate factor scores for the construction of the investor sentiment composite index.

Table 5.32 Factor Loadings for PC1 and PC2

	1	**2**
$TURN^{C}_{t-1}$	0.957	0.135
$NIPO^{C}_{t}$	-0.251	0.796
$RIPO^{C}_{t}$	0.297	0.704
ADV^{C}_{t}	0.399	-0.191
CSI^{C}_{t-1}	0.963	0.113

Note: Superscript C represents cleaner proxy net macroeconomic fundamentals.

Another interesting fact to address is the correlation between each proxy and the cleaner investor sentiment composite index, illustrated in the second column of Table 5.32. Focusing on the first principal component (PC1), one-month-lag CSI and TURN are highly correlated with the cleaner index. Compared to raw proxy correlations with ISCI (Table 5.27), both cleaner measures of TURN and CSI maintain their timings of one-month lag to the index. CSI continues to have the strongest correlation with the cleaner index, while TURN seems to have a weaker net macroeconomic fundamental correlation. This finding suggests that among macroeconomic fundamentals, CSI has the least influence, although it measures the perception of consumers towards future economic conditions. CSI may be a good representation of investor sentiment; however, it is published only on a quarterly basis. Additionally, major changes are observed in NIPO and RIPO where NIPO turns into an inverse relationship (ρ=-0.251) in its correlation with cleaner investor sentiment index.

Another interesting finding is the comparison between the effect of cleaner ADV and the raw proxy reported in an earlier section. As shown in Table 5.27, raw ADV correlates the least (ρ=0.01) with the raw investor sentiment composite index. However, it grows stronger after the effect of macroeconomic fundamentals is removed. The findings justify the proposition by Baker and Wurgler (2007) that proxies have to be individually regressed with macroeconomic fundamentals, rather than the index as a whole. This is because each proxy may experience a different and unique effect by the economy. Some proxies are strongly influenced by the economy while others may be more strongly influenced by non-fundamental factors. The $ISCI^C$ is computed as weighted standardised cleaner proxies from Table 5.32 from 2000-2012. Therefore, the parsimonious equation for cleaner sentiment index is:

$$ISCI_t^C = 0.44TURN_{t-1}^C - 0.172NIPO_t^C + 0.092RIPO_t^C + 0.2ADV_t^C + 0.445CSI_{t-1}^C \tag{45}$$

The cleaner investor sentiment composite index (ISCI^C) on monthly frequency is then plotted as shown in Figure 5.9. Throughout 2000-2012, the ISCI^C seems to be consistent except for a few periods of apparent negative sentiment observed from April 2002 to August 2002, November 2007 to March 2009, and from March 2010 to January 2011.

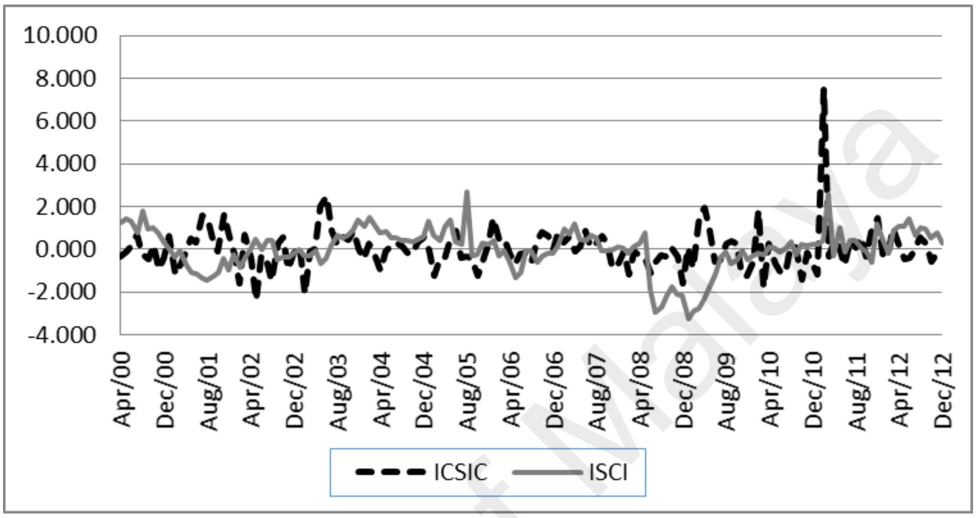


Figure 5.9 ISCI and ISCI^C Movement for 2000-2012

The next section investigates the relationship between ISCI and ISCI^C and the leading stock market barometer, the Kuala Lumpur Composite Index (KLCI), its returns (RKLCI), and volatility (VKLCI).

Descriptive Analyses and Relationships between ISCI, ISCI^C and KLCI, RKLCI, and VKLCI

Previous research has studied the relationship between sentiment and stock market returns in environments such as the United States and other developed markets. The present study establishes the development of an investor sentiment composite index with specific focus on the Malaysian stock market; this is likely to provide significant insight into other emerging economies as well. This section begins with the descriptive analysis of each variable, the basic test being for data normality. As shown in Table

5.33, all five variables are expected to have non-normal distribution of data, which is evident from the values of mean, median, skewness, and kurtosis as warranted by the Jarque-Bera statistic. The hypothesis that the data are normally distributed is rejected at the 1% significance level.

Table 5.33 Descriptive Analysis of VKLCI, RKLCI, ISCI, and ICSI^C

	VKLCI	RKLCI	KLCI	ISCI	ISCI^C
Mean	0.004	0.002	1052.813	0.000	-0.016
Median	0.004	0.005	927.540	-0.083	0.050
Maximum	0.012	0.055	1688.950	7.500	2.666
Minimum	0.001	-0.072	572.880	-2.370	-3.280
Std. Dev.	0.002	0.020	323.608	1.000	1.003
Skewness	1.252	-0.497	0.378	2.774	-0.806
Kurtosis	4.396	4.083	1.786	22.462	4.464
Jarque-Bera	52.377***	13.783***	13.03***	2610.941***	30.231***
Observations	153	153	153	153	153
ADF:					
with drift	-7.56***	-10.783***	0.228	-11.297***	3.31***
with drift and trend	-8.054***	-10.789***	-2.737	-11.258***	-3.273*
without drift and trend	-1.429	-10.708***	1.437	11.334***	-3.315***
PP:					
with drift	-8.007***	-10.776***	-0.18	-11.314***	-4.405***
with drift and trend	-8.589***	-10.782***	-3.105	-11.276***	-4.373***
l Drift and trend	-2.803***	-10.739***	1.062	-11.351***	-4.419***

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are tests for unit root.

With regards to tests of stationarity, ADF and PP statistics for VKLCI, RKLCI, ISCI, and ISCI^C consistently reject the null hypothesis that there is unit root in each of its residuals. Each variable is modelled without drift and trend, with drift and with drift and trend. The results justify that the variables are integrated at levels or I(0). The following test involves the study of correlations between the variables, and is illustrated in Table 5.34.

Table 5.34 Correlations between KLCI, ISCI, ISCI^C, RKLCI, and VKLCI

	KLCI	ISCI	ISCI^C	RKLCI	VKLCI
KLCI	1.000				
ISCI	-0.082	1.000			
ISCI^C	0.224**	0.003	1.000		
RKLCI	-0.030	0.229***	-0.186**	1.000	
VKLCI	-0.357***	0.115	-0.171**	-0.078	1.000

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

One of the main objectives of this study is to examine the correlation effect of explanatory variables on the volatility of KLCI. Thus, the results in Table 5.34 are discussed in relation to VKLCI, which is part of meeting objective two. It is observed that KLCI and ISCI^C hold significant negative correlations with VKLCI. With any increase in KLCI, VKLCI decreases by 35.7%. Being the cleaner index for investor sentiment, ISCI^C also declines by 17.1%, which possibly means that whenever VKLCI moves positively, investor sentiment becomes calmer. There are also strong correlations between ISCI and ISCI^C and RKLCI; an increase in RKLCI results in increase in ISCI as well. An increase in RKLCI results in a decrease in the cleaner investor sentiment composite index (ISCI^C).

These findings could mean that increase in stock market returns would result in an increase in macroeconomic-influenced investor sentiment. However, the net macroeconomic investor sentiment results in lower mood. This finding is inconsistent with previous literature (Baker and Wurgler, 2007; Verma and Verma, 2007). This may be due to inaccuracy of the raw ISCI as representative of true investor sentiment, since it is highly influenced by macroeconomic factors in Malaysia. This justifies the construction of the cleaner investor sentiment composite index. Nevertheless, since correlations do not measure causality, they do not take into account errors while computing the relationship; hence further tests are examined in detail in the following section.

5.6 The Investor Sentiment Composite Index and Volatility of KLCI

5.6.1 During the Whole Period of Study (2000-2012) [RQ2(i)]

This part of the analysis tests the predictive power of the investor sentiment composite index, raw and net macroeconomic fundamentals over the volatility of the Malaysian stock market. The second statistical hypothesis is:

H2(i): The investor sentiment composite index has no significant causal relationship with the volatility of KLCI for the whole period of study (2000-2012).

Recapitulating from Table 5.33, all variables except KLCI are stationary in nature, implying that there are no issues of spurious regression to test the relationship between investor sentiment indices and VKLCI. Therefore, the simple VAR or ARDL in levels can be applied to model the relationships (Asteriou and Hall, 2007). Prior to modelling any distributive lag model including VAR, it is crucial to determine optimal lags of the variables. Optimal lag selection contributes to the accuracy of the forecasting model where it varies substantially for alternative lag length (Hafer and Sheehan, 1989). Nevertheless, one has to be careful not to select a high order, since that tends to cause an increase in the mean square forecast errors of VAR; and under-fitting the lag length often generates auto-correlated errors (Lutkepohl, 1993).

In line with the analysis discussed, the relationship between ISCI and $ISCI^{C}$, VKLCI is modelled using VAR with different orders from lag 1 to 12. The maximum lag of twelve is chosen in order to be consistent with the monthly frequency data used in this study. The results computed by AIC and SC are illustrated in Table 5.35; R^2 represents the model's goodness of fit.

Table 5.35 Lag Selection Criteria

Number of lags	R^2	AIC	SC
1	0.24	-9.544	**-9.464**
2	0.27	-9.547	-9.407
3	0.299	-9.547	-9.346
4	0.313	-9.523	-9.261
5	0.379	-9.581	-9.257
6	0.413	**-9.67**	-9.285
7	0.415	-9.637	-9.188
8	0.436	-9.624	-9.11
9	0.451	-9.612	-9.035
10	0.447	-9.581	-8.938
11	0.457	-9.554	-8.846
12	0.456	-9.513	-8.739

Note: Figures in bold denote the lowest values of AIC and SC.

As observed in literature, SC-based criteria typically select a much shorter lag than AIC-based criteria. Accordingly, VAR models with lag 1 and lag 6 are selected by AIC and SC respectively (Table 5.35). As reported in previous studies, there are inconsistencies in the selection of optimal lags by both AIC and SC. In agreement with Shibata (1983), the importance of selecting optimal criteria does not rely on the consistency of the procedure, but is an inevitable association in balancing under-fitting and over-fitting risks. Variable lags would have to be modelled and checked with stability analysis with regards to suggestions provided by AIC and SC.

Using minimum AIC and SC procedures, the models are therefore fitted into a sample of 3 series: VKLCI, ISCI, and $ISCI^C$ from 153 monthly time series. Since the results would differ along with the arrangement of the variables into VAR function in EViews

8, it is important to maintain the order arrangement throughout the analysis in order to avoid inconsistency in results. For analysis throughout this section, the arrangement is VKLCI, ISCI, and ISCI^{C}, as proposed by AIC and SC. Nevertheless, one disadvantage of the VAR models is that the obtained coefficients are difficult to interpret due to the lack of a theoretical background. In order to countervail potential criticism, it is important to estimate causality in VAR models. Developed by Granger (1969), the causality test is defined as follows: a variable Y_t is said to be Granger caused by X_t if Y_t can be predicted with greater accuracy by using past values of the X_t variable, when all other variables remain unchanged.

$$VKLCI_t = \alpha_1 + \sum_{i=1}^{n} \beta_i ISCI_{t-1} + \sum_{j=1}^{n} \beta_2 ISCI^{C}{}_{t-j} + \sum_{j=1}^{n} \beta_3 VKLCI_{t-j} + \varepsilon_{1t} \tag{46}$$

The null and alternated hypotheses are:

H$_0$: $\sum_{i=1}^{n} \beta_i = 0$ or X_t does not cause $\mathrm{Y_t}$

H$_1$: $\sum_{i=1}^{n} \beta_i \neq 0$ or X_t does cause $\mathrm{Y_t}$

Results for all three variables throughout the period of study according to each lag are presented in Table 5.36. Values in asterisk denote that the null hypothesis is rejected, thus supporting a causal relationship between the variables. Since one of the objectives of the study is to peruse the predictive power of investor sentiment over stock market volatility, this study justifies the selection of a VAR model in analysing the data.

Table 5.36 Granger Causality Relationship (2000-2012) between VKLCI, ISCI, and ISCI^C with Respective Lags

Y_t	X_{t-j}	$\chi2$	Lags	Y_t	X_{t-j}	$\chi2$	Lags
VKLCI	ISCI	1.251	1	VKLCI	ISCI	11.145	7
	ISCI^C	2.631*	1		ISCI^C	15.244***	7
ISCI	VKLCI	0.008	1	ISCI	VKLCI	8.428	7
	ISCI^C	0.847	1		ISCI^C	2.577	7
ISCI^C	VKLCI	0.573	1	ISCI^C	VKLCI	10.026	7
	ISCI	10.717***	1		ISCI	21.539***	7
VKLCI	ISCI	2.0427	2	VKLCI	ISCI	11.536	8
	ISCI^C	3.456	2		ISCI^C	15.986**	8
ISCI	VKLCI	5.823**	2	ISCI	VKLCI	8.163	8
	ISCI^C	1.373	2		ISCI^C	1.62	8
ISCI^C	VKLCI	0.806	2	ISCI^C	VKLCI	10.34	8
	ISCI	16.711***	2		ISCI	20.695***	8
VKLCI	ISCI	1.309	3	VKLCI	ISCI	13.212	9
	ISCI^C	3.75	3		ISCI^C	17.895**	9
ISCI	VKLCI	6.348*	3	ISCI	VKLCI	7.936	9
	ISCI^C	1.725	3		ISCI^C	1.418	9
ISCI^C	VKLCI	3.392	3	ISCI^C	VKLCI	14.854*	9
	ISCI	19.272***	3		ISCI	23.911***	9
VKLCI	ISCI	1.28	4	VKLCI	ISCI	12.98	10
	ISCI^C	4.797	4		ISCI^C	19.14**	10
ISCI	VKLCI	6.912	4	ISCI	VKLCI	10.01	10
	ISCI^C	1.839	4		ISCI^C	4.447	10
ISCI^C	VKLCI	5.287	4	ISCI^C	VKLCI	15.066	10
	ISCI	20.067***	4		ISCI	26.262***	10
VKLCI	ISCI	3.916	5	VKLCI	ISCI	13.835	11
	ISCI^C	12.221**	5		ISCI^C	21.034***	11
ISCI	VKLCI	7.026	5	ISCI	VKLCI	7.878	11
	ISCI^C	2.128	5		ISCI^C	5.522	11
ISCI^C	VKLCI	8.372	5	ISCI^C	VKLCI	15.053	11
	ISCI	20.280***	5		ISCI	23.315***	11
VKLCI	ISCI	11.134*	6	VKLCI	ISCI	13.529	12
	ISCI^C	18.12***	6		ISCI^C	21.081**	12
ISCI	VKLCI	7.982	6	ISCI	VKLCI	8.244	12
	ISCI^C	2.765	6		ISCI^C	5.507	12
ISCI^C	VKLCI	9.3	6	ISCI^C	VKLCI	15.826	12
	ISCI	19.759***	6		ISCI	23.334**	12

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.

Table 5.36 presents the predictive power of ISCI and ISCI^C over VKLCI in their respective lag until the maximum lag of twelve. In accordance with row 1 of Table 5.36, the hypothesis that there is no Granger causality between ISCI^C is rejected at the 10% level of significance. It is therefore observed that at lag 1, the cleaner index of investor sentiment significantly Granger-causes volatility in KLCI. The effect disappears with the increase of lags until the re-appearance of Granger causality in lag 5, as shown in row 26. It is apparent that the hypothesis is rejected at the 5% level of significance for Granger causality of ISCI^C to VKLCI. The ISCI^C Granger-causes the volatility of KLCI from lag 5 until the maximum lag of 12. Therefore, there is evidence that the predictability of the cleaner index of investor sentiment over stock market volatility is significant in longer horizons. These results are consistent with what is reported by Baker and Cliff (2005). Using direct surveys as proxy for investor sentiment, they found that it could predict market returns over a period of 1 to 3 years. Findings from the present study may conclude similar suggestions.

In checking for robustness in this study, the relationship is tested with the ARDL model. Prior to that, it is crucial to determine optimal lags suggested by the AIC and SC criteria. ARDL models with respective lags are estimated, and the optimal lag is selected when the model estimates the lowest values of AIC and SC. Table 5.37 presents the results.

Table 5.37 Lag Selection Criteria for ARDL Model

Lags	R^2	AIC	SC	DW	LR test	ARCH
1	0.256	-9.533	-9.413	2.19	17.672	0.181
2	0.294	-9.543	-9.363	2.06	11.93	0.0083
3	0.312	-9.538	-9.297	2.04	11.934	0.217
4	0.325	-9.514	-9.212	2.08	30.275***	0.266
5	0.391	-9.573	-9.209	2.06	18.995*	1.102
6	0.425	**-9.665**	**-9.491**	2.03	9.05	3.00
7	0.426	-9.628	-9.429	1.98	9.102	3.955*
8	0.447	-9.614	-9.06	1.98	11.406	3.017*
9	0.464	-9.61	-8.991	2.04	7.339	3.251*
10	0.463	-9.582	-8.898	2.00	6.82	3.13*
11	0.47	-9.55	-8.802	1.98	8.009	2.415
12	0.47	-9.512	-8.697	1.99	6.877	3.727**

Note: Figures in bold denote the lowest value of AIC and SC. *, **, and *** denote significance levels of 1%, 5%, and 10% respectively.

In accordance with consistent suggestions by AIC and SC, the lowest values given for the model are at lag 6, as displayed in Table 5.37. The final model is free from autocorrelation and the presence of an ARCH effect, as evidenced by the LR and ARCH test statistics. As proposed by the criteria in Table 5.37, the results of ARDL (5,6,6) are reported in Table 5.38.

Table 5.38 ARDL (5,6,6) Model with Lags (2000-2012) Proposed by AIC and SC

Variables	Coefficients	Standard Error	t-statistic
C	0.0014***	0.0005	2.8147
$VKLCI_{t-1}$	0.187**	0.084	2.23
$VKLCI_{t-2}$	0.0943	0.0834	1.13
$VKLCI_{t-3}$	0.117	0.0839	1.319
$VKLCI_{t-4}$	0.09	0.0843	1.068
$VKLCI_{t-5}$	0.1452*	0.0843	1.722
ISCI	0.0003	0.00015	1.619
$ISCI_{t-1}$	-0.00086	0.00016	-0.536
$ISCI_{t-2}$	-0.0001	0.00016	-0.656
$ISCI_{t-3}$	0.00014	0.00017	0.8237
$ISCI_{t-4}$	-0.00005	0.00017	0.3079
$ISCI_{t-5}$	0.0003	0.00016	1.5418
$ISCI_{t-6}$	0.0004**	0.00016	2.2513
$ISCI^{C}$	-0.00003	0.00028	-0.1269
$ISCI^{C}_{t-1}$	0.000025	0.0003	0.0808
$ISCI^{C}_{t-2}$	-0.004	0.0003	-1.2752
$ISCI^{C}_{t-3}$	-0.005*	0.0003	-1.686
$ISCI^{C}_{t-4}$	-0.0003	0.0003	-0.6714
$ISCI^{C}_{t-5}$	4.00E-04	0.0003	1.2094
$ISCI^{C}_{t-6}$	0.0005**	0.0003	2.0339
R^2	0.4251	D.W	2.03
AIC	-9.6648	SC	-9.2376

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.
Superscript C represents cleaner proxy net macroeconomic fundamentals.

ISCI and $ISCI^{C}$ are the two focus variables in this study that significantly affect the volatility of KLCI in longer horizon (lag 6), as illustrated in Table 5.38. This finding suggests significant predictive power of investor sentiment measured by ISCI and $ISCI^{C}$ over VKLCI – which is consistent with the findings modelled by VAR in Table 5.36. Therefore, VAR and ARDL observe that both sentiment indices are able to predict the volatility of KLCI on a longer horizon beginning six-month period of study. A convincing result that justifies the construction of the cleaner investor sentiment composite index manifests at lag 3. It is evident that post removal of macroeconomic fundamental influences from the raw index, investor sentiment has emerged as a significant predictor of volatility at the near-term of 3 months. This finding rejects hypothesis 2(i); investor sentiment does significantly affect the volatility of Malaysian stock market for the period of study.

5.6.2 Global Financial Crisis [RQ2(ii)]

With regards to research question 2(ii), a co-integration test is not required to test the relationship, since all variables involved are stationary in nature. Hence, a VAR model is sufficient to model the relationship in sub-period analysis, particularly the global financial crisis. However, since the VAR model is atheoretical, it is better to examine the relationship between variables by Granger causality. Table 5.39 presents the Granger causal relationships between ISCI, $ISCI^{C}$, and VKLCI. The statistical hypothesis tested is:

H2(ii): The investor sentiment composite index has no significant causal relationship with the volatility of KLCI during the global financial crisis.

Table 5.39 Granger Causality (2008 Global Financial Crisis) between ISCI, $ISCI^C$, and VKLCI

Y_t	X_{t-j}	$\chi2$	Lags	Y_t	X_{t-j}	$\chi2$	Lags
VKLCI	ISCI	0.615	1	VKLCI	ISCI	8.184	6
	$ISCI^C$	0.110	1		ISCIC	12.35**	6
ISCI	VKLCI	1.047	1	ISCI	VKLCI	6.713	6
	$ISCI^C$	0.136	1		$ISCI^C$	3.442	6
$ISCI^C$	VKLCI	0.007	1	$ISCI^C$	VKLCI	12.245	6
	ISCI	4.026**	1		ISCI	3.175	6
VKLCI	ISCI	1.697	2	VKLCI	ISCI	10.200	7
	$ISCI^C$	0.917	2		$ISCI^C$	9.359	7
ISCI	VKLCI	2.828	2	ISCI	VKLCI	7.757	7
	$ISCI^C$	0.767	2		$ISCI^C$	2.689	7
$ISCI^C$	VKLCI	0.347	2	$ISCI^C$	VKLCI	6.194	7
	ISCI	1.950	2		ISCI	2.455	7
VKLCI	ISCI	4.541	3	VKLCI	ISCI	36.338***	8
	$ISCI^C$	2.051	3		$ISCI^C$	21.616***	8
ISCI	VKLCI	2.961	3	ISCI	VKLCI	3.352	8
	$ISCI^C$	0.662	3		$ISCI^C$	1.509	8
$ISCI^C$	VKLCI	11.565***	3	$ISCI^C$	VKLCI	3.742	8
	ISCI	3.149	3		ISCI	0.696	8
VKLCI	ISCI	6.215	4	VKLCI	ISCI	68.434***	9
	$ISCI^C$	2.219	4		$ISCI^C$	49.13***	9
ISCI	VKLCI	2.913	4	ISCI	VKLCI	3.362	9
	$ISCI^C$	0.654	4		$ISCI^C$	3.482	9
$ISCI^C$	VKLCI	8.442**	4	$ISCI^C$	VKLCI	41.365***	9
	ISCI	4.405	4		ISCI	19.161**	9
VKLCI	ISCI	7.989	5				
	$ISCI^C$	10.599*	5				
ISCI	VKLCI	6.701	5				
	$ISCI^C$	2.300	5				
$ISCI^C$	VKLCI	9.675*	5				
	ISCI	2.693	5				

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

The predictive power of both ISCI and $ISCI^C$ over VKLCI manifests during a longer horizon. This result is consistent with previous findings for the period of study (2000-2012). Row 26 of Table 5.39 is evidence that at lag 5, $ICSI^C$ significantly Granger-causes the volatility of KLCI. The causal relationship continues at lag 6, disappears at lag 7, and resumes from lag 8 to lag 9. Interestingly, lag 5 and 6 evidence a bi-directional causal relationship between $ISCI^C$ and VKLCI. In order to justify the findings from VAR model reported in Table 5.39, a robustness test is performed. In order to maintain consistency with previous analyses, the ARDL (p,q) model is adopted with a maximum of 7 lags, constrained by a small number of samples identified earlier. Multiple experiments are conducted to reach the optimum number of lags for each variable, until the smallest AIC and SC values are obtained. Table 5.40 presents the final ARDL (4,7,4) model which illustrates the relationship between ISCI and $ISCI^C$ and VKLCI.

Table 5.40 ARDL (4,7,4) Model (2008 Global Financial Crisis) between ISCI, $ISCI^C$ and VKLCI

Variable	Coefficient	t-Statistic	Variable	Coefficient	t-Statistic
C	0.022***	5.7338	$ISCI_{t-5}$	-0.00015	-0.2333
$VKLCI_{t-1}$	-0.608**	-2.8876	$ISCI_{t-6}$	0.0004	0.5694
$VKLCI_{t-2}$	-0.528**	-2.4242	$ISCI_{t-7}$	-0.001*	-1.9676
$VKLCI_{t-3}$	-0.555**	-2.6077	$ISCI^C_t$	0.002**	2.3044
$VKLCI_{t-4}$	-0.618**	-2.8083	$ISCI^C_{t-1}$	-0.0018	-1.5158
$ISCI_t$	-0.0002	-0.3782	$ISCI^C_{t-2}$	0.0014	1.2123
$ISCI_{t-1}$	-0.002**	-2.8384	$ISCI^C_{t-3}$	-0.0006	-0.6431
$ISCI_{t-2}$	-0.0011	-1.6854	$ISCI^C_{t-4}$	-0.002**	-2.4913
$ISCI_{t-3}$	-0.0009	-1.3957	@TREND	-0.0003***	-3.7045
$ISCI_{t-4}$	-0.0023***	-3.5262			
R^2	0.774		DW	1.87	
AIC	-9.447		LM Test	0.118	
SC	-8.568		ARCH Test	0.0004	

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

The final ARDL (4,7,4) model illustrated in Table 5.40 reveals that macroeconomic-influenced investor sentiment and the cleaner index of investor sentiment have a significant effect on the volatility of KLCI. Interestingly, the effect of the cleaner investor sentiment composite index on the volatility of KLCI is contemporaneous during the global crisis, which suggests that investor sentiment is more influenced by irrational behaviour rather than by macroeconomic fundamentals. In conclusion, during the 2008 global financial crisis, the effect of investor sentiment sustained its significance and improved its predictive value. Therefore, hypothesis 2(ii) is rejected, and answer the second research question.

5.7 The Investor Sentiment Composite Index and Volatility of Malaysian Stock Returns Controlled by Macroeconomic Fundamentals and the Sub-Period of the Global Financial Crisis (RQ3)

5.7.1 Controlled by Macroeconomic Fundamentals [RQ3(i)]

As a robustness test of the predictive value of the investor sentiment composite indices, the relationship between the raw and cleaner versions of the index is modelled with the inclusion of macroeconomic fundamentals as control variables. This step is taken in order to justify the consistency and significance of the constructed investor sentiment index to the movement of the stock market. The statistical hypothesis is stated as:

H3(i): Investor sentiment has no significant causal relationship with the volatility of KLCI when controlled by macroeconomic fundamentals.

As tested in the earlier part of this chapter, macroeconomic variables comprise of a number of variables that are order-integrated at levels I(0), while others are order-integrated at I(1). As proposed by Pesaran et al. (2001), the ARDL model bound test approach is the best method to examine long-run and short-run relationships between variables of different order integration. In this study, ARDL model has been used for a number of applications, whether it is a simple ARDL (p,q) model or an ARDL model that is able to examine co-integration between variables. This part of the analysis is expected to test the third hypothesis: whether investor sentiment retains its significant predictive value over the volatility of KLCI when controlled by macroeconomic fundamentals and the period of the global financial crisis. The variables are modelled by VAR for each individual lag up to a maximum of twelve lags for monthly frequency data. This step is taken in order to identify optimal lags suggested by AIC and SC selection criteria. As VAR is atheoretical in nature, the analysis resumes with the Granger causality test in order to obtain a clearer description of the relationships. The hypothesis is that X_{t-j} does not Granger-cause Y_t, and the relationship is suggested by χ^2 statistics. The hypothesis is rejected if the calculated χ^2 statistics exceed critical values at 1%, 5%, and 10%. Table 5.41 exhibits the Granger causality between the explanatory variables and the volatility of KLCI. Asterisks suggest significant values of χ^2 with their respective lags.

Table 5.41 Granger Causality Relationship (2000-2012) between ISCI, ISCI^C, Macroeconomic Fundamentals, and VKLCI with respective lags

Y_t	X_{t-j}	χ^2	Lags	X_{t-j}	χ^2	Lags
VKLCI	ISCI	0.9106	1	ISCI	11.3542	7
	ISCI^C	3.7013**	1	ISCI^C	7.8984	7
	BLR	0.091	1	BLR	12.6969*	7
	EER	0.542	1	EER	13.1374	7
	M3	0.7971	1	M3	9.9451	7
	CPI	0.0083	1	CPI	14.2546	7
	IPI	6.3228***	1	IPI	1.1586	7
	ISCI	0.8024	2	ISCI	11.6462	8
	ISCI^C	5.183*	2	ISCI^C	7.4721	8
	BLR	2.5663	2	BLR	14.48618*	8
	EER	0.0684	2	EER	15.0463*	8
	M3	0.7234	2	M3	8.9984	8
	CPI	4.5163	2	CPI	13.78907*	8
	IPI	5.7086**	2	IPI	1.5145	8
	ISCI	0.7673	3	ISCI	12.6678	9
	ISCI^C	6.1264	3	ISCI^C	8.1327	9
	BLR	4.6414	3	BLR	16.38583*	9
	EER	1.7852	3	EER	12.6412	9
	M3	6.7367*	3	M3	8.2564	9
	CPI	5.0677	3	CPI	10.3510	9
	IPI	5.5043	3	IPI	3.5514	9
	ISCI	5.3155	4	ISCI	18.7478	10
	ISCI^C	6.4858	4	ISCI^C	7.8130	10
	BLR	5.6593	4	BLR	24.2665***	10
	EER	6.8006	4	EER	16.9953*	10
	M3	18.3748***	4	M3	13.6609	10
	CPI	6.3083	4	CPI	17.005*	10
	IPI	2.0463	4	IPI	3.3329	10
	ISCI	5.484	5	ISCI	12.5525	11
	ISCI^C	12**	5	ISCI^C	11.7896	11
	BLR	9.9572*	5	BLR	24.3751	11
	EER	6.0989	5	EER	19.28879*	11
	M3	17.0048***	5	M3	13.7534	11
	CPI	13.4052***	5	CPI	14.8833	11
	IPI	1.4039	5	IPI	6.2350	11
	ISCI	11.6959*	6	ISCI	11.6896	12
	ISCI^C	11.3099*	6	ISCI^C	12.6904	12
	BLR	11.7503*	6	BLR	13.5453	12
	EER	10.9268*	6	EER	12.6938	12
	M3	13.6139**	6	M3	13.4781	12
	CPI	15.4476***	6	CPI	11.1656	12
	IPI	1.4146	6	IPI	5.5114	12

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

As seen in Table 5.42, ISCI^C Granger-causes the volatility of KLCI with 5% and 1% significance levels at lag 1 and lag 2. However, the effect disappears, then re-emerges at lag 5 and lag 6. The results are consistent with previous findings reported in the earlier part of this chapter, such as reports from Table 5.38 and 5.39, where both Granger causality as well as ARDL suggested parsimonious models at lag 6.

However, since the variables are a mixture of different orders of integration, it is prudent to model the predictive relationship with ARDL. One of the advantages is that ARDL allows for dynamic relationship between variables with I(0) and I(1), as long they do not reach I(2). Apart from that, different variables can also be assigned different lags as they are entered into a model. Despite the advantages of ARDL, the over-establishment of maximum lags to model ARDL results in loss in the degree of freedom, a possible multi-colinearity, and severe autocorrelation. Therefore, it is important not to overestimate maximum lags in the ARDL model. Throughout this chapter, AIC and SC have been used as criteria for lag selection. AIC and SC suggested lag 6 in modelling the predictive relationship. Nevertheless, it is noteworthy that in accordance with Pesaran and Shin (1997), SC is generally preferred over other criteria, as it tends to define more parsimonious specifications. In modelling the predictive relation between variables with different orders of integration, the ARDL (6,6,6) test of co-integration with bound test is selected. The ARDL model is as follows:

$$\begin{aligned}\Delta VKLCI_t &= \alpha_0 + \alpha_1 VKLCI_{t-1} + \alpha_2 ISCI_{t-1} + \alpha_3 ISCI^C_{t-1} + \alpha_4 BLR_{t-1} + \alpha_5 CPI_{t-1} + \alpha_6 EER_{t-1} \\ &+ \alpha_7 IPI_{t-1} + \alpha_8 M3_{t-1} + \beta_i \Delta VKLCI_{t-i} + \beta_j \Delta ISCI_{t-j} + \beta_k \Delta ISCI^C_{t-k} + \beta_l \Delta BLR_{t-l} + \beta_m \Delta CPI_{t-m} \\ &+ \beta_n \Delta EER_{t-n} + \beta_p \Delta IPI_{t-p} + \beta_q \Delta M3_{t-q} + \varepsilon_t \end{aligned} \quad (47)$$

Table 5.42 presents results from the ARDL (6,6,6,6,6,6,6,6) model with significant coefficients marked with asterisks that indicate significance levels of 1%, 5%, and 10%. In the ARDL model, $\alpha_1 VKLCI_{t-1}$, $\alpha_2 ISCI_{t-1}$, $\alpha_3 ISCI^C_{t-1}$, $\alpha_4 BLR_{t-1}$, $\alpha_5 CPI_{t-1}$, $\alpha_6 EER_{t-1}$,

$\alpha_7 IPI_{t-1}$, and $\alpha_8 M3_{t-1}$ are the co-integrating equation regression. This is the first part of the equation that Pesaran et al. (2001) regard as the conditional error correction model, which is similar to VECM. In order to detect the co-integrating relationship, the bound test is applied to the equation to test the joint hypothesis that the coefficients of $VKLCI_{t-1}$, $\alpha_1 ISCI_{t-1}$, $ISCI^{C}_{t-1}$, BLR_{t-1}, CPI_{t-1}, EER_{t-1}, IPI_{t-1}, and $M3_{t-1}$ are zero.

Table 5.42 ARDL (6,6,6,6,6,6,6,6) Model (2000-2012) between ISCI and ISCI^C and KLCI Controlled by Macroeconomic Fundamentals

Variables	Coefficient	Std. Error	t-Statistic	Variable	Coefficient	Std. Error	t-Statistic	Variables	Coefficient	Std. Error	t-Statistic
C	-0.25299	0.19434	-1.3018	$\Delta ISCI^C_t$	0.00013	0.00031	0.4090	ΔEER_{t-1}	-0.13908***	0.05069	-2.7435
$VKLCI_{t-1}$	-1.04135***	0.27443	-3.7946	$\Delta ISCI^C_{t-1}$	0.00048	0.00039	1.2403	ΔEER_{t-2}	0.04456	0.04760	0.9362
$ISCI_{t-1}$	0.00102**	0.00044	2.3004	$\Delta ISCI^C_{t-2}$	0.00018	0.00040	0.4507	ΔEER_{t-3}	-0.05771	0.04394	-1.3134
$ISCI^C_{t-1}$	-0.00053*	0.00029	-1.8103	$\Delta ISCI^C_{t-3}$	-0.00028	0.00039	-0.7018	ΔEER_{t-4}	-0.02203	0.04597	-0.4793
BLR_{t-1}	0.00871**	0.00403	2.1586	$\Delta ISCI^C_{t-4}$	-0.00061*	0.00038	-1.5896	ΔEER_{t-5}	0.02518	0.04491	0.5607
CPI_{t-1}	-0.00292	0.00238	-1.2257	$\Delta ISCI^C_{t-5}$	0.00011	0.00037	0.2917	ΔEER_{t-6}	-0.00434	0.04582	-0.0946
EER_{t-1}	-0.00112	0.02648	-0.0423	$\Delta ISCI^C_{t-6}$	0.00009	0.00030	0.2802	ΔIPI_t	0.00329	0.01166	0.2817
IPI_{t-1}	0.01035	0.01489	0.6949	ΔBLR_t	0.00813	0.00570	1.4258	ΔIPI_{t-1}	-0.00376	0.01737	-0.2166
$M3_{t-1}$	0.04311	0.02703	1.5947	ΔBLR_{t-1}	-0.00033	0.00646	-0.0506	ΔIPI_{t-2}	-0.00641	0.01799	-0.3564
$\Delta VKLCI_{t-1}$	0.19109	0.25404	0.7522	ΔBLR_{t-2}	-0.00152	0.00651	-0.2329	ΔIPI_{t-3}	0.00533	0.01798	0.2967
$\Delta VKLCI_{t-2}$	0.09181	0.23530	0.3902	ΔBLR_{t-3}	-0.00458	0.00586	-0.7824	ΔIPI_{t-4}	0.00638	0.01774	0.3594
$\Delta VKLCI_{t-3}$	0.14889	0.20617	0.7222	ΔBLR_{t-4}	-0.00404	0.00602	-0.6722	ΔIPI_{t-5}	-0.00250	0.01603	-0.1559
$\Delta VKLCI_{t-4}$	0.01545	0.17663	0.0875	ΔBLR_{t-5}	0.01489***	0.00572	2.6060	ΔIPI_{t-6}	-0.00073	0.01123	-0.0649
$\Delta VKLCI_{t-5}$	0.00205	0.13583	0.0151	ΔBLR_{t-6}	-0.00642	0.00595	-1.0786	$\Delta M3_t$	0.109**	0.05143	2.1197
$\Delta VKLCI_{t-6}$	0.00073	0.09334	0.0078	ΔCPI_t	-0.00481*	0.00278	-1.7290	$\Delta M3_{t-1}$	-0.13867***	0.05326	-2.6037
$\Delta ISCI_t$	0.00000	0.00016	-0.0085	ΔCPI_{t-1}	0.00831***	0.00314	2.6504	$\Delta M3_{t-2}$	-0.00333	0.05192	-0.0641
$\Delta ISCI_{t-1}$	-0.00091**	0.00037	-2.4532	ΔCPI_{t-2}	0.00064	0.00296	0.2155	$\Delta M3_{t-3}$	0.01204	0.05111	0.2355
$\Delta ISCI_{t-2}$	-0.00099***	0.00033	-2.9478	ΔCPI_{t-3}	0.00469	0.00290	1.6156	$\Delta M3_{t-4}$	0.01290	0.05236	0.2464
$\Delta ISCI_{t-3}$	-0.00069**	0.00030	-2.3106	ΔCPI_{t-4}	-0.00390	0.00290	-1.3442	$\Delta M3_{t-5}$	0.02043	0.05173	0.3950
$\Delta ISCI_{t-4}$	-0.00082***	0.00027	-3.0171	ΔCPI_{t-5}	0.00121	0.00284	0.4260	$\Delta M3_{t-6}$	-0.09972**	0.04956	-2.0121
$\Delta ISCI_{t-5}$	-0.0006***	0.00023	-2.6530	ΔCPI_{t-6}	0.00354	0.00270	1.3126	@Trend	-0.00021**	0.00010	-2.0524
$\Delta ISCI_{t-6}$	-0.00023	0.00017	-1.3472	ΔEER_t	0.06038	0.04330	1.3947				

R^2	0.7421	DW	2.043
AIC	-9.772	LM Test	13.991 (p-value 0.3013)
SC	-8.44	ARCH Test	1.492 (p-value 0.1299)

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

The critical values in Table 5.12 under unrestricted intercept and unrestricted trend are 2.38, 3.45 (10%), 2.69, 3.83 (5%), 3.34, and 4.63 (1%) for the lower bound and the upper bound respectively. Using the Wald test, the F-statistic is calculated at 3.162 (p-value=0.007), and is greater than the lower bound I(0) of 10% critical values, with k=7. Thus, the null hypothesis is not rejected, implying that the variables have a long-run co-integrating relationship. The relationship between each explanatory variable with lags and VKLCI is tested by the Wald analysis. The hypothesis is that the joint coefficient of lags of the same variable is zero. This result suggests short-run dynamics between the variables. The significance of the short-run dynamic between variables is determined by testing the joint hypothesis of lags variables. The findings are presented in Table 5.43.

Table 5.43 Joint Hypotheses of Explanatory Variables with Computed F-statistic

Variables	**F-statistic**
$VKLCI_{t-1}$, $\alpha_1 ISCI_{t-1}$, $ISCI^C_{t-1}$, $LBLR_{t-1}$, $LCPI_{t-1}$, $LEER_{t-1}$, $LIPI_{t-1}$, $LM3_{t-1}$	3.162***
$\Delta VKLCI_{t-1}$, $\Delta VKLCI_{t-2}$, $\Delta VKLCI_{t-3}$, $\Delta VKLCI_{t-4}$, $\Delta VKLCI_{t-5}$, $\Delta VKLCI_{t-6}$	0.403
$\Delta ISCI_t$, $\Delta ISCI_{t-1}$, $\Delta ISCI_{t-2}$, $\Delta ISCI_{t-3}$, $\Delta ISCI_{t-4}$, $\Delta ISCI_{t-5}$, $\Delta ISCI_{t-6}$	1.905*
$\Delta ISCIC_t$. $\Delta ISCIC_{t-1}$, $\Delta ISCIC_{t-2}$, $\Delta ISCIC_{t-3}$, $\Delta ISCIC_{t-4}$, $\Delta ISCIC_{t-5}$, $\Delta ISCIC_{t-6}$	1.036
$\Delta LBLR_t$, $\Delta LBLR_{t-1}$, $\Delta LBLR_{t-2}$, $\Delta LBLR_{t-3}$, $\Delta LBLR_{t-4}$, $\Delta LBLR_{t-5}$, $\Delta LBLR_{t-6}$	1.748
$\Delta LCPI_t$, $\Delta LCPI_{t-1}$, $\Delta LCPI_{t-2}$, $\Delta LCPI_{t-3}$, $\Delta LCPI_{t-4}$, $\Delta LCPI_{t-5}$, $\Delta LCPI_{t-6}$	1.712
$\Delta LEER_t$, $\Delta LEER_{t-1}$, $\Delta LEER_{t-2}$, $\Delta LEER_{t-3}$, $\Delta LEER_{t-4}$, $\Delta LEER_{t-5}$, $\Delta LEER_{t-6}$	1.438
$\Delta LIPI_t$, $\Delta LIPI_{t-1}$, $\Delta LIPI_{t-2}$, $\Delta LIPIt\text{-}3$, $\Delta LIPI_{t-4}$, $\Delta LIPI_{t-5}$, $\Delta LIPI_{t-6}$	0.252
$\Delta LM3_t$, $\Delta LM3_{t-1}$, $\Delta LM3_{t-2}$, $\Delta LM3_{t-3}$, $\Delta LM3_{t-4}$, $\Delta LM3_{t-5}$, $\Delta LM3_{t-6}$	2.019*

Note: ***, ** and * denote significant levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

It is apparent from Table 5.43 that apart from a significant F-statistic for the long-run co-integrating relationship, the lagged coefficients of ISCI and LM3 also reject the null hypothesis. This suggests that there are short-run dynamics between ISCI and LM3 concerning VKLCI. In order to cross-check the existence of the long-run co-integrating relationship, the model of ARDL (6,6,6,6,6,6,6,6) from Table 5.42 is re-estimated where the insignificant lags of each variable are removed from the equation until a variable with significant lag is presented. This results in the selection of an ARDL (5,4,5,2,1,0,1) specification with the lowest estimation from the SC criterion of -9.19. The final ARDL model is free from autocorrelation and heteroscedasticity as shown by the LM and ARCH test statistics in Table 5.44.

Table 5.44 Final Equilibrium Co-integrating ARDL (5,4,5,2,1,0,1) Model (2000-2012)

Variable	Coefficient	Std. Error	t-Statistic	Variable	Coefficient	Std. Error	t-Statistic
C	-0.18416	0.12008	-1.534	$\Delta ISCI^C_{t-1}$	0.00057*	0.00030	1.884
$VKLCI_{t-1}$	-0.9452***	0.11477	-8.237	$\Delta ISCI^C_{t-2}$	0.00030	0.00031	0.957
$ISCI_{t-1}$	0.0007*	0.00035	1.937	$\Delta ISCI^C_{t-3}$	-0.00009	0.00030	-0.315
$ISCI^C_{t-1}$	-0.0005***	0.00021	-2.401	$\Delta ISCI^C_{t-4}$	-0.00044*	0.00026	-1.735
$LBLR_{t-1}$	0.0078***	0.00261	2.990	$\Delta LBLR_t$	0.00343	0.00496	0.692
$LCPI_{t-1}$	-0.00187	0.00118	-1.592	$\Delta LBLR_{t-1}$	-0.00011	0.00501	-0.021
$LEER_{t-1}$	-0.00113	0.01562	-0.072	$\Delta LBLR_{t-2}$	-0.00307	0.00476	-0.645
$LIPI_{t-1}$	0.00826	0.00842	0.981	$\Delta LBLR_{t-3}$	-0.00191	0.00488	-0.392
$LM3_{t-1}$	0.0313*	0.01767	1.769	$\Delta LBLR_{t-4}$	-0.00458	0.00481	-0.951
$\Delta VKLCI_t$	0.06895	0.08318	0.829	$\Delta LBLR_{t-5}$	0.0118**	0.00451	2.615
$\Delta ISCI_t$	0.00011	0.00014	0.813	$\Delta LCPI_{t-1}$	-0.00258	0.00219	-1.177
$\Delta ISCI_{t-1}$	-0.0005*	0.00029	-1.812	$\Delta LCPI_{t-2}$	0.00623***	0.00205	3.043
$\Delta ISCI_{t-2}$	-0.0006***	0.00026	-2.561	$\Delta LEER_t$	0.0688*	0.03659	1.882
$\Delta ISCI_{t-3}$	-0.00045**	0.00023	-1.969	$\Delta LEER_{t-1}$	-0.095***	0.03757	-2.538
$\Delta ISCI_{t-4}$	-0.00055***	0.00019	-2.925	$\Delta LIPI_t$	0.00209	0.00846	0.246
$\Delta ISCI_{t-5}$	-0.00033**	0.00014	-2.368	$\Delta LM3_t$	0.1436***	0.03949	3.637
$\Delta ISCI^C_t$	-0.00002*	0.00026	-0.083	$\Delta LM3_{t-1}$	-0.1321***	0.04170	-3.169
				@TREND	-0.00016	0.00006	-2.516
R^2	0.66779			DW	2.043		
AIC	-9.907864			LM Test	13.991 (0.3013)		
SC	-9.195857			ARCH Test	1.492(0.1299)		

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

As presented in Table 5.44, the long-run multiplier between ISCI and VKLCI is 0.00074, computed as [-(0.0007/-0.9452)]. This suggests that in the long-run, an increase of 1% in investor sentiment will lead to an increase of 0.074% in the volatility of KLCI. There is also a significant relationship between $ISCI^C$ and VKLCI, where an increase of 1% in the cleaner index of investor sentiment will lead to a decrease of 0.053% in the volatility of KLCI. The estimation of ECM and results are shown in

Table 5.45. The model is also tested for autocorrelations and heteroscedasticity by the ARCH test. It is by far the model with the lowest SC value in selection of lags.

Table 5.45 Long-run Equilibrium Model (2000-2012) with Restricted ECM

Variable	Coefficient	Std. Error	t-Statistic	Variable	Coefficient	Std. Error	t-Statistic
Z_{t-1}	-0.8513***	0.10419	-8.1709	$\Delta LBLR_t$	0.0044	0.0048	0.9147
$\Delta VKLCI_t$	0.0352	0.07914	0.4446	$\Delta LBLR_{t-1}$	-0.0018	0.0047	-0.3863
$\Delta ISCI_t$	0.00005	0.00013	0.3558	$\Delta LBLR_{t-2}$	-0.0049	0.0046	-1.0870
$\Delta ISCI_{t-1}$	-0.00017	0.00016	-1.0610	$\Delta LBLR_{t-3}$	-0.0022	0.0047	-0.4631
$\Delta ISCI_{t-2}$	-0.0004**	0.00017	-2.1926	$\Delta LBLR_{t-4}$	-0.0049	0.0046	-1.0836
$\Delta ISCI_{t-3}$	-0.0002	0.00017	-1.2457	$\Delta LBLR_{t-5}$	0.0114***	0.0044	2.6078
$\Delta ISCI_{t-4}$	-0.0004***	0.00015	-2.5208	$\Delta LCPI_{t-1}$	-0.001	0.0019	-0.5483
$\Delta ISCI_{t-5}$	-0.0003**	0.00013	-1.9336	$\Delta LCPI_{t-2}$	0.0041**	0.0018	2.2191
$\Delta ISCI^C_t$	0.00003	0.00023	0.1394	$\Delta LEER_t$	0.0694	0.0350	1.9785
$\Delta ISCI^C_{t-1}$	0.00024	0.00024	0.9696	$\Delta LEER_{t-1}$	-0.073**	0.0358	-2.0511
$\Delta ISCI^C_{t-2}$	-0.00005	0.00025	-0.2070	$\Delta LIPI_t$	-0.0071	0.0073	-0.9743
$\Delta ISCI^C_{t-3}$	-0.0004	0.00026	-1.3418	$\Delta LM3_t$	0.1188	0.0331	3.5863
$\Delta ISCI^C_{t-4}$	-0.0006***	0.00024	-2.3890	$\Delta LM3_{t-1}$	-0.136***	0.0340	-3.9975
R^2	0.632143			D.W	1.95		
AIC	-9.928389			LM Test	10.437(0.577)		
SC	-9.399469			ARCH Test	0.199(0.655)		

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively.
Superscript C represents cleaner proxy net macroeconomic fundamentals.

Note that the coefficient of the error correction term, Z_{t-1} is negative and significant, which means that there is a co-integrating relationship between the variables. This finding is consistent with the results of long-run equilibrium between ICSI, $ISCI^C$, BLR, CPI, EER, IPI, M3, and VKLCI in the final ARDL model (Table 5.45). The magnitude of this coefficient (Z_{t-1}=-0.8513) also implies that 0.85% of any disequilibrium between the variables is corrected within a period of one-month. The results reject hypothesis 3(i), leading to the conclusion that the cleaner proxy for investor sentiment maintains its significance in predicting the volatility of KLCI as early as 4 months in advance, even when it is controlled by macroeconomic variables.

5.7.2 Controlled by the sub-period of the Global Financial Crisis [RQ3(ii)]

Since multiple structural breaks were identified throughout the period of study (2000-2012), it is critical to determine whether the breaks have an impact on the volatility of KLCI. The present study, however, focuses on the impact of the global financial crisis, which falls between January 2007 and February 2010. This is justified by the Bai-Perron structural test. The statistical hypothesis tested is stated as:

H3(ii): Investor sentiment has no significant causal relationship with the volatility of KLCI when controlled by the sub-period of the global financial crisis.

This step involves modelling the relationship between ISCI, $ISCI^C$, and VKLCI with VAR and ARDL lags consistent with the suggested optimal lags by AIC and SC in Table 5.37. The determinant residual covariance from the VAR model with dummy and without dummy is extracted in order to calculate the likelihood ratio (LR) statistic. The values are given in Table 5.46, where the calculated LR statistic is 46.38, exceeding the chi-square critical value.

Table 5.46 Effect of the Global Financial Crisis on the VAR Model

	VAR with Dummy	VAR without Dummy
Number of observations	147	147
Lags	6	6
Determinant residual covariance	0.00000052	0.00000076
LR statistic	46.38	
Chi-square critical value	1% - 11.34; 5% - 7.82, 10% - 6.25	

Judging by the calculated LR statistic, the hypothesis that the global financial crisis has no effect on the VAR model is rejected. The 2008 global financial crisis has a significant impact on the VAR model. However, in order to test for the robustness of this effect, the ARDL model is again applied to observe the effect of the global financial crisis on the volatility of the stock market. An ARDL (5,6,6) test consistent with the suggested selection of AIC and SC lags from Table 5.37 is modelled with an additional dummy variable added into the equation. The results are as illustrated in Table 5.47.

Table 5.47 ARDL (5,6,6) Model with Global Crisis and Lags Suggested by AIC and SC

Variables	Coefficient	Standard Error	t-Statistic
C	0.0013***	0.0004	2.800
$VKLCI_{t-1}$	0.1422*	0.0831	1.7116
$VKLCI_{t-2}$	0.0804	0.0814	0.9870
$VKLCI_{t-3}$	0.1016	0.0819	1.2401
$VKLCI_{t-4}$	0.0868	0.0822	1.0560
$VKLCI_{t-5}$	0.1439*	0.0822	1.7505
ISCI	0.0003*	0.0001	1.8028
$ISCI_{t-1}$	-0.00005	0.0001	-0.3540
$ISCI_{t-2}$	-0.00008	0.0001	-0.5492
$ISCI_{t-3}$	0.00013	0.0001	0.8168
$ISCI_{t-4}$	0.00005	0.0001	0.3017
$ISCI_{t-5}$	0.0002	0.0001	1.5006
$ISCI_{t-6}$	0.0003**	0.0001	2.2026
$ISCI^{C}_{t}$	0.00003	0.0002	0.1320
$ISCI^{C}_{t-1}$	0.00005	0.0003	0.1733
$ISCI^{C}_{t-2}$	-0.00036	0.0003	-1.2099
$ISCI^{C}_{t-3}$	-0.0005*	0.0003	-1.7294
$ISCI^{C}_{t-4}$	-0.0002	0.0003	-0.6733
$ISCI^{C}_{t-5}$	0.0004	0.0002	1.3246
$ISCI^{C}_{t-6}$	0.0006**	0.0003	2.4220
Global Financial Crisis	0.001***	0.0004	2.7569

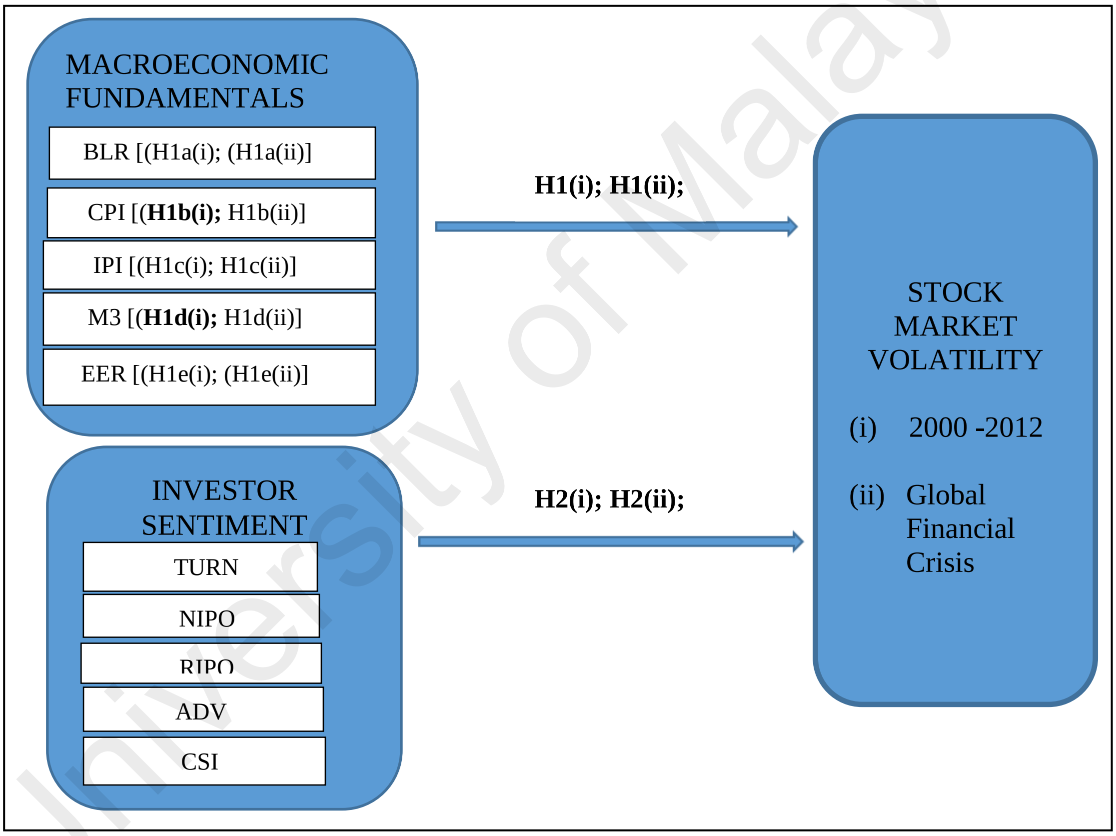
Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively. Superscript C represents cleaner proxy net macroeconomic fundamentals.

With reference to Table 5.47, the cleaner investor sentiment composite index maintains its significant predictive value over the volatility of KLCI at lag 3 and lag 6, which is consistent with Table 5.38, thus rejecting hypothesis 3(ii) and answering the third research question. Nevertheless, the global financial crisis has significant positive effect on the volatility of KLCI. The ARDL (5,6,6) model is free from autocorrelation in its residuals, as measured by the insignificant LM statistic (χ^2=8.853). Therefore, the result justifies the findings of the global financial impact that affected the VAR model mentioned earlier.

5.8 Summary

This chapter explores possible statistical analyses to explore potential determinants of Malaysian stock market volatility. Since each variable is of different characteristics as reported by the descriptive analysis, specific types of models are tested to determine the relationships. The associations between variables are mainly modelled with VAR, Granger causal relationship, and the ARDL model. It can be concluded that there is no short-run relationship between macroeconomic fundamentals and the volatility of the stock market during the global financial crisis. However, generally, for the period from 2000-2012, inflation rate and broad money supply significantly predict the volatility of KLCI. The variables also have an equilibrium relationship in the long-run. In order to examine the causal relationship between non-fundamental factors and the volatility of the stock market, this study proposes the construction of an investor sentiment composite index. The construction of the index is required since there is no direct measurement of investor sentiment available for stock markets in Malaysia. The final constructed composite index comprises of five proxies: stock market turnover, number of IPOs, the initial returns of IPOs, advancer/decliner stock ratios, and the consumer sentiment index.

The cleaner measure of the composite index, which is free from the influence of macroeconomic fundamentals, is also constructed. Results show that the cleaner composite index of investor sentiment has significant predictive power over the volatility of the stock market on longer horizon, from a period of six to twelve months. Finally, robustness tests reveal that the significant ability of investor sentiment to predict the volatility of KLCI is sustained, even when the models are controlled by the global financial crisis as well as the inclusion of macroeconomic fundamentals. The effect can also be observed when the sample period is constrained to the 38 months of the global financial crisis from 2008 to 2010. Figure 5.10 and Table 5.48 present the summary of research and statistical hypotheses with observed results. The listed statistical hypotheses are represented by null hypotheses that lead to rejection in favour of alternate hypotheses (demonstrated in bold) in Figure 5.10.



Note: Statistically significant relationships are denoted in bold.
Figure 5.10 Summary of Results from Tested Hypotheses

Table 5. 48 Summary of Hypotheses and Results

Hypotheses	**Results**
H1(i): Macroeconomic fundamentals (BLR, CPI, IPI, M3, and EER) have no significant causal relationship with the volatility of KLCI during the Whole period of study (2000-2012).	*Reject H_0 (CPI, M3 and IPI)* *Failed to Reject H_0 (BLR and EER)*
H1(ii): Macroeconomic fundamentals (BLR, CPI, IPI, M3, and EER) have no significant causal relationship with the volatility of KLCI during the period of the 2008 global financial crisis.	*Failed to Reject H_0*
H2(i): Investor sentiment has no significant causal relationship with the volatility of KLCI for the Whole period of study (2000 – 2012).	*Reject H_0*
H2(ii): Investor sentiment has no significant causal relationship with the volatility of KLCI during the 2008 global financial crisis.	*Reject H_0*
H3(i): Investor sentiment has no significant causal relationship with the volatility of KLCI when controlled by macroeconomic fundamentals.	*Reject H_0*
H3(ii): Investor sentiment has no significant causal relationship with the volatility of KLCI when controlled by the global financial crisis.	*Reject H_0*

CHAPTER 6: DISCUSSION AND CONCLUSION

6.1 Introduction

The purpose of this chapter is to recapitulate the significant phases of this study; findings are summarised and implications are discussed. The findings of the research are then compared and contrasted with previous studies that were presented in the review of literature. This chapter also includes a discussion of the limitations of the study, as well as recommendations for future research.

This work provides an insight into the determinants of stock market volatility, utilising fundamental as well as non-fundamental paradigms. Previous studies examine whether macroeconomic fundamentals contribute to determining the movement of stock prices. These studies mainly seek to justify the contribution of the well-known efficient market hypothesis and asset pricing behaviour. If determinant factors are able to predict incoming irrational behaviour of the market, measures can be taken by policymakers or practitioners towards adopting possible tools and strategies to contain the erratic movement of the stock market. Since the volatility of stock markets is not entirely explained by macroeconomic fundamentals, recent studies suggest studying the contribution of non-fundamental explanations which include the irrational behaviour of investors. One of the purposes of this study is to examine the explanation that investor sentiment, being a non-fundamental factor, has a significant effect on stock market price movement. However, this presents a challenge for interested researchers, since the measurement of investor sentiment is yet to be definitive. Practitioners define investor sentiment as the mood of investors towards conditions of the stock market, while scholars have different definitions. The lack of agreeable definition makes it crucial to compose an appropriate definition and measure from available proxies, in order to represent investor sentiment – especially in the Malaysian stock market.

This study begins by examining the effect of macroeconomic fundamentals on the volatility of the stock market. Although this study proceeds from previous empirical research based on a similar platform, it applies a different statistical methodology. Secondly, the existence of non-fundamental factors is tested to investigate their relationship with the volatility of the stock market. The particular objective of this study is to determine if such factors explain the volatility of KLCI, and whether they can be adopted as a tool by researchers and practitioners to explain stock market movements, both for the period of study (2000-2012) and the 2008 global financial crisis. This issue requires appropriate definition and measurement to represent investor sentiment as a non-fundamental factor in the Malaysian stock market. This issue leads to the identification of appropriate proxies to represent investor sentiment.

The investor sentiment composite index is therefore constructed from five available proxies adopted from the Bursa Malaysia equity data and a consumer sentiment index constructed by MIER. Various robustness tests are then conducted on the constructed investor sentiment composite index. The measures are targeted to examine the ability of the constructed index to predict the volatility of the stock market in Malaysia. The procedure involves the inclusion of the 2008 global financial crisis and macroeconomic fundamentals as control variables. Findings from these tests seek to answer all research questions with appropriate data and research methodology, as discussed in Chapter Four.

In fulfilling the first research objective (the relationship between macroeconomic fundamentals and KLCI volatility), VECM and ARDL (p,q) statistical causal relationship are adopted. This is to address the problem of inconsistencies of order integration of each variable. Results from the models are reported and discussed for comparison. The second research objective concerns possible non-fundamental determinant factors of the volatility of the stock market. The determination of an appropriate measure of non-fundamental factors in this study requires the construction of an index based on available proxies.

A total of five proxies are combined into a single factor via factor analysis, extracted with principal component analysis. Each proxy is tested for unit root, normality, and correlation with volatility. The final constructed investor sentiment composite index is then regressed with macroeconomic variables in order to obtain an index free from the influence of macroeconomic fundamentals. The research resumes with testing the predictive value of the composite index over the volatility of KLCI. The methodology is rather straightforward, as both variables are stationary in nature, and do not require complex models such as the VECM. This relationship is observed via the simple ARDL (p,q) and VAR models with Granger causality. In terms of robustness checks, the constructed investor sentiment composite index is tested against the volatility of KLCI, controlled for macroeconomic fundamentals and the 2008 global financial crisis. The tests are conducted separately; the relationship controlled for macroeconomic fundamentals is modelled with the ARDL (p,q) bound-test model, while the relationship controlled for the 2008 global financial crisis is modelled with VAR, owing to several reasons mentioned in Chapter Four. This step is undertaken due to the nature of each series of different order integration. A final test is conducted to study the relationship between the constructed composite index for the period of the 2008 global financial crisis. In line with the stationary nature of the series involved in this test, the relationship is modelled by VAR with the assistance of Granger causality, coupled with the application of the ARDL (p,q) model as to be consistent with other relationship tests. The results and basic analyses, along with respective tables, are presented in

Chapter Five, which analyses the findings in detail by taking into account previous studies as discussed in Chapter Two.

6.2 Discussion of Findings

This section discusses the findings of the study by linking the results to previous studies with regard to the effect of macroeconomic fundamentals on volatility of the stock market, and investor sentiment during the period of study and during the global financial crisis of 2008-2010.

6.2.1 Macroeconomic Fundamentals and Malaysian Stock Market Volatility for the Whole Period of Study and the Global Financial Crisis [RO1(i) and RO1(ii)]

The analysis in the study is divided into two parts: first, the correlation between each variable and the volatility of KLCI; and second, the causal relationship between macroeconomic variables and the volatility of KLCI. From the analysis results, it is found that the short-term interest rate (BLR), real output growth rate (IPI), and broad money supply rate (M3) significantly co-move with the volatility of the stock market. This result provides promising preliminary insights into the relationship between macroeconomic fundamentals and stock market volatility. Previous empirical studies have focussed on the causal relationship between these variables and stock market volatility. For instance, Zakaria and Shamsuddin (2012) found that fluctuations in short-term interest and inflation rates had a causal effect on fluctuations in the stock market. However, it is worthy to highlight several limitations of the methodology undertaken by Zakaria and Shamsuddin (2012). Their study measures the fluctuation of KLCI in monthly frequency with the GARCH (1,1) model. However, as discussed in Chapter Five of this thesis, the clustering effect becomes subtle due to the low frequency of data.

Another factor to be questioned in their research is the adoption of the Malaysian ringgit to the U.S. dollar as the unit for exchange rate, whereby Malaysia pegged its currency to the U.S. dollar at MYR3.80 between the period of 1998-2005. Therefore, it is not surprising that not much movement was observed in the data, and the measurement of volatility in their study is questionable.

As an extension of Zakaria and Shamsuddin (2012), this study examined the effect of many other macroeconomic variables on the volatility of the stock market in addition to testing short-term interest and inflation rates. The relationship was tested by applying VECM to long-run as well as short-term causal relationships. The causal VECM relationship test showed a significant long-run causal relationship between short-term interest rate, inflation rate, exchange rate, and broad money supply and the volatility of the stock market. However, there was only significant dynamic causal relationships between inflation rate and growth of money supply in the economy with the volatility of the stock market. It is worth noted that, with the application of VECM time-series model, contradictory result was observed, whereby only the economy output rate significantly predicted stock market volatility. This shows that there are inconsistencies in findings with different statistical methodologies. Employing the ARDL (p,q) model for the period of study(2000-2012), results show a negative relationship between industrial production index and stock market volatility, which is consistent with the findings of Hosseini, Ahmad, and Lai (2011) on China's stock market index. However, it is inconsistent with their findings on data from India. From a broader perspective, Davis and Kutan (2003) found marginal predictive power between macroeconomic variables and stock market volatility in 12 developed countries. They report that only a few countries had predictive values with real output over stock market volatility, used as an endogenous variable along with inflation rate. Thus, it may be concluded that previous empirical findings are inconsistent with findings on Malaysian stock market in term of the variables and the direction of relationships, although similarities exist in the measurement of variables. This is supported by Hosseini et al. (2011), who conclude that the impact of macroeconomic variables varies between countries.

In contrast to the effect of macroeconomic fundamentals on stock market volatility throughout the period of the study, the period of the global financial crisis shows no causal relationship effect at all. This warrants the inclusion of the effect of non-fundamental variables on the volatility of the stock market, as proposed by Angabini and Wasiuzzaman (2011) and Law (2006) specifically during periods of crisis. This is consistent with previous findings with regard to short-term dynamics between variables. Schwert (1989) acknowledges that stock market volatility was higher during crises compared to periods of economic tranquillity. Yet, alternative determinants of excess volatility were not explored further, even though they found weak evidence for the volatility of macroeconomic variables predicting stock market volatility.

6.2.2 Investor Sentiment and Malaysian Stock Market Volatility for the Whole Period of Study and During the Global Financial Crisis [RO2(i) and RO2(ii)]

The second research objective seeks to examine the relationship between investor sentiment and stock market volatility by looking at correlations and causal relationships. Thus far, the current study has been novel in this approach in terms of its measurement of investor sentiment, the proxies included in the construction of the investor sentiment composite index, and significant findings during the period of the global financial crisis.

Although the proxies and methodology of analysis applied in this thesis differ, similar results have been observed in other studies. Investor sentiment is negatively related to the volatility of the stock market, which is consistent with results produced by Verma and Verma (2007). A possible explanation for this is that investors tend to keep away from the stock market, resulting in low volume and creating higher volatility of stock prices owing to larger bid-ask price spread.

As theoretically posited by DeLong, Shleifer, Summers, and Waldmann (1990), noise traders believe that they have special information about the future price of risky assets. They receive these pseudo-signals from technical analysts, stockbrokers, or from economic consultants, and react accordingly. The effects create their own risk, which tends to reduce the attractiveness of arbitrage. By and large, in the absence of fundamental risks, arbitrageurs have limited opportunities due to the difficulty in liquidating their investment in short horizons, thus creating larger divergences from their fundamental values, which yields higher returns for noise traders. Divergence thus explains the prolonged higher returns and volatility of stock prices that still exists in the longer horizon.

The second research objective of this study involves predicting the causal relationship of the constructed investor sentiment composite index to the volatility of the stock market. As tested in previous hypotheses, the cleaner investor sentiment composite index seems to prove its effectiveness as an appropriate index to represent investor sentiment in the Malaysian stock market. The investor sentiment composite index manages to predict the volatility of the stock market as early as three to six months for the entire period of 13 years of the study. Due to the encouraging evidence, this study takes a step further by specifically examining whether the predictive value of the investor sentiment composite index retains its effectiveness during the financial crisis, and, if the predictive value is affirmative, what the direction of the relationship is.

In conclusion, the predictive power of investor sentiment retains its effectiveness during financial crisis, where, interestingly, the predictability of stock market volatility appears sooner than during the rest of the period of study. In the context of relationships, it is found that investor sentiment moves in the direction opposite to the volatility of the stock market index. The inverse relationship is consistent with previous studies by Verma and Verma (2007) that have been discussed in the earlier section of this chapter. It can be conjectured that the higher the sentiment of investors, the less volatile is the stock market. In other words, low sentiment of investors increases stock market volatility. This finding is consistent with previous studies of Lee, Jiang, and Indro (2002) and Verma and Verma (2007). This is also supported by Ho and Hung (2012), who found that shifts in investor sentiment affected conditional volatility of the stock market in countries such as the United States and Italy, being developed markets. They further extended the study on the predictive power of investor sentiment over subsequent stock returns to other countries, including France.

It is evident that volatility during financial crises is unusually high. One of the causes of this was the irrational behaviour of investors in anticipation of further decline of stock prices. This is suggested by Law (2006) in his study on the level of volatility in the Malaysian stock market which increased substantially during the 1997-1998 Southeast Asian financial crisis. This may be explained by the behaviour of investors, who were traumatised by the performance of the aggregate market, manifesting a downtrend in KLCI. As shown in Figure 5.1 and 5.5, the volatility of KLCI was apparent during the period. It reached its highest in October 2008.

The most significant contribution of this thesis is evidence for the apparent existence of investor sentiment during global financial crisis in 2008, representing a non-fundamental factor. This finding has by far never been reported in any empirical research, in developed or developing stock markets. This opens a window of opportunity for further exploration in this area of research. As illustrated in Table 5.40, the ARDL (4,7,4) model evidences significant negative effect between the cleaner investor sentiment composite index and volatility of the stock market. The effect provides additional information, since the main objective is to examine the predictive power of investor sentiment over the volatility of the stock market.

6.2.3 Investor Sentiment and Malaysian Stock Market Volatility Controlled by Macroeconomic Fundamentals [RO3(i)] and the Global Financial Crisis [RO3(ii)]

Another robustness test to check the effectiveness of the constructed investor sentiment composite index is carried out in which macroeconomic fundamentals are selected as control variables in the model. The variables include short-term interest rate, inflation rate, currency exchange rate, output growth rate, and money supply rate. Results show that all variables, including the investor sentiment composite indices and macroeconomic variables, have significant long-run causal relationships. Of all the models that are examined, only the raw investor sentiment composite index possesses strong short-term causal relationships with stock market volatility. The index, which is heavily influenced by macroeconomic fundamentals, significantly predicts the volatility of the stock market from as close as a one-month period to a five-month period. Inverse relationships between raw investor sentiment and the volatility of the stock market are observed due to macroeconomic factors embedded in the index. Therefore, the relationship is biased, and is not accepted as evidence in this study.

The "cleaner" investor sentiment composite index, on the other hand, shows no evidence of strong relationships between the proxies, contrary to the observation of the raw investor sentiment composite index in the development of the investor sentiment composite index. This establishes that the cleaner investor sentiment index is free from the influence of macroeconomic fundamentals, and should be adopted as the appropriate measurement of investor sentiment. As shown in Table 5.44 of the analysis, the cleaner investor sentiment composite index is able to predict the volatility of the stock market one and four months ahead. The relationships are significant regardless of whether macroeconomic fundamentals are taken as control variables. Findings from this study are disparate with Baker and Wurgler (2006) in two ways. Firstly, Baker and Wurgler (2006) studied the relationship between the sentiment index and stock returns, while this study focuses on the volatility of stock returns. Secondly, Baker and Wurgler's (2006) proxies were not as highly influenced by macroeconomic fundamentals as in this study. As shown in Table 5.28 in Chapter Five, the correlation between the raw and cleaner investor sentiment composite index only yielded about 0.003, which is positive but not significant. This is due to the inability of some of the proxies to retain the signs and timing regarding the composite sentiment index after the influence of macroeconomic fundamentals are removed. It can be concluded that all proxies in this study, except consumer sentiment index, are highly influenced by macroeconomic fundamentals.

In summary, investor sentiment is able to predict the occurrence of financial crisis in advance, and that policymakers should not ignore signs indicated by the constructed index. Although the world equity sentiment index observes no similarity to the constructed investor sentiment composite index in this study, the basic ideas complement one another. Both observe the possible predictive value of investor sentiment on crises in the financial market. This study extends it further, leading to the conclusion that investor sentiment is able to predict volatility of the stock market as early as three months in advance. The robustness test includes checking the effectiveness of the investor sentiment composite index in predicting the volatility of the stock market during episodes of crisis.

6.3 Conclusion

For the period of study 2000-2012, inflation rate and broad money supply representing fundamental factors prove to be good predictors of stock market volatility for a month in advance. On the other hand, investor sentiment has predictive value in the longer horizon of three months and farther. The results suggest that fundamental and non-fundamental factors complement each other in determining stock market volatility. This relationship manifests in a single model discussed in section 5.7.3, where investor sentiment, interest rate, inflation rate, exchange rate, and the circulation of money in the economy are contemporaneously significant predictors of stock market volatility.

With regard to excessive stock market prices, the findings of this study are consistent with the suggestions of previous studies (Law, 2006; Shiller, 1981; Zakaria and Shamsuddin, 2012) that excessive volatility of the stock market may be explained by the irrational behaviour of investor sentiment. This is evident from the inadequacy of macroeconomic variables in predicting the volatility of the stock market, although investor sentiment significantly predicts volatility on the longer horizon. The findings support the notion that investors in developing countries are possibly highly influenced by non-fundamental news, which eventually manifests in their irrational behaviour, especially during crises (Angabini and Wasiuzzaman, 2010). This behaviour may be further explained with the notion that Asian investors tend to be overconfident in making decisions due to a socially collective paradigm in collective-oriented societies (Chui, Titman, and Wei, 2010; Kim and Nofsinger, 2008).

The study further extends the analysis to focus on the behaviour of stock market volatility over the limited period of the 2008 global crisis, during which higher volatility of the stock market has been observed. It is one of the periods that investors feared the most, as it translates to uncertainty in the future direction of stock prices. Although economic data in Malaysia do not show any alarming figures, investor reactions reflected the experience of the United States stock market almost instantaneously. The movement of major stock market indices was unstable for a long period around the crises, as shown in Figure 1.1. Thus, volatility in the Malaysian stock market was the highest from 2008-2010 (Figure 5.4). All these factors drive the need to identify causes of the behaviour, so that it helps academics and practitioners better understand the stock market.

As documented in previous studies, the stock market reaches abnormal levels of volatility during financial crises (Cuñado and Gracia, 2008; Edwards, 2003). Hence, it is interesting to identify the causes of excess volatility. There are no known previous studies that utilise a similar methodology – except a study by Bandopadhyaya and Truong (2010), which is by far the closest to this study. They constructed a world equity market sentiment index from nine global market indices, and found that prior to the financial crisis in the United States, market sentiment has acted according to the findings of the current study.

6.4 Implications of the Study

Volatility of the stock market may create panic among investors, and such fears can impact the stock market itself. If the situation is not controlled, the effect can become worse. A possible cause of the inevitable volatility is the news, whether it is fundamentally-based or merely rumours. Regardless of the status of the information, news can be contagious. Therefore, the determinant factors of stock market volatility is an important area to be explored, and findings have several important implications for participants of the equity market, for policymakers and academicians.

6.4.1 Theory

It is established in modern portfolio theory that stock markets are said to be efficient when no factor can explain or predict their movement. In most traditional finance theories, the contribution of investor sentiment has been rejected. This traditional approach is adopted due to the belief that asset prices are rational assessments of expected future payoffs. With the assumption that there are no frictions in the competitive market, the price of a security should equal its fundamental value (Fama, 1970). The efficient market hypothesis also believes that any abnormality is quickly adjusted in its price with the assistance of arbitrage opportunity. Nevertheless, given the results from this study, it is apparent that the combination of macroeconomic fundamentals and investor sentiment systematically explains the movement of the Kuala Lumpur Composite Index, therefore rejecting the notion that the Malaysian stock market is efficient. This is supported by a study by Tham, Azizan, and Lau (2012), who found the opportunity to exploit stock returns by adopting technical analysis to make systematic abnormal profits in investment.

From the perspective of behavioural finance, there is always the possibility of non-fundamental factors in determining asset pricing, which is due to the correlated trading activities of unpredictable noise traders. The behaviour of noise traders makes it difficult to diversify away investment risks. Findings from this study provide evidence that in the longer horizon, non-fundamental factors – specifically, investor sentiment – succeed in explaining and predicting the volatility of the Malaysian stock market. Generally, it can be concluded that the stock market in Malaysia is inefficient to a certain extent, since it affords opportunities to predict the market and possibly obtain abnormal returns.

Findings from this study support the behavioural finance theory, particularly in the case of financial crises, where changes in dividends or macroeconomic fundamentals fail to be explained by Shiller (1981). The stock market tends to exhibit persistent excessive volatilities, which are unable to be explained by market fundamentals alone. It is very likely that the stock market is swayed by the powerful emotions of extreme nervousness and anxiety among its participants. In particular, findings from this thesis support the behavioural capital asset pricing theory developed by Shefrin and Statman (1994) from the evidence that in addition to fundamental variables, investor sentiment could consistently predict the movement of stock market volatility, and this can be measured in a single time-series model.

In conclusion, as mentioned in Chapter One, the purpose of this study is not to discard conventional asset pricing theory and the efficient market hypothesis, but to seek the connection between conventional and behavioural finance theories in predicting stock market volatility. Findings from this study provide evidence that both theories complement each other in the real-world environment.

6.4.2 Policymakers

From a broader perspective, findings from this study have significant implications for policymakers such as the Central Bank and the Malaysian stock market exchange. The Central Bank needs to cautiously decide on possible measures to avoid the negative impact of stock market volatility on other sectors in economy. One of the possible measures is to take into consideration the consequences of each approach to maintain or improve the country's economic condition. For example, in many countries, central banks set the short-term interest rates for overnight borrowing for banks, which may cause the stock market to react violently. Findings from this study therefore suggest as to which variables are worth looking into, and what conditions will are likely to lead to; and which information is crucial to the Government in formulating policies.

As a policymaker in the equity market, Bursa Malaysia would want to be aware of factors of concern in order to control excess volatility in the stock market. Findings from this study suggest that in order to form new policies, Bursa Malaysia should focus on the effect of inflation and money supply activity on stock market volatility. This is the crucial period when effective approaches have to be applied in conjunction with appropriate tools to eradicate irrational reactions from stock market sentiments. Additionally, in expectation of the irrational movement of the stock prices, an early intervention from policymakers can also be carried out.

Currently, a number of regulated measures are implemented by Bursa Malaysia in order to curb stock market volatility. These include "circuit breakers", which halt trading once a 10% drop in the stock market takes place. It is designed to maintain market stability and to provide stock market participants with access to new information before making investment decisions. In particular, should the KLCI fall 10% or more from the previous day's closing level, the circuit breaker is automatically triggered, following which the market is halted for a specific period of time.

Another measure is the price-limit pressure, which restricts the movement of individual stocks to a threshold of 30% upward and downward per trading session. Price limits help mitigate default risk by applying a cap on daily price changes. Proponents of the trading halt (circuit breaker) contend that it provides time for investors to process new information, which promotes an orderly market and maintains price stability. Opponents, however, argue that a trading halt delays stock price adjustment and increases post-halt trading volatility (Kim and Rhee, 1997). A more recent study on emerging markets finds that trading volume and volatility are abnormally high immediately after trading on an order-driven market (Frino, Lecce, and Segara, 2011). Therefore, policymakers need to look into efficient measures to dampen the volatility of the stock market, as suggested by this study.

6.4.3 Stock Market Participants

Findings from this study also have significant implications for stock market participants, comprising of investors and speculators. These findings potentially help investors in deciding on appropriate investment strategies to implement in forming their investment portfolios for different stock market conditions. It is worthwhile for investors to understand as to which fundamental or non-fundamental factors affect the volatility of the stock market. With enlightenment from the findings of this study, investors are likely to be aware of their financial surroundings, being equipped with strategies prior to available announcements. All kinds of economic data disclosed by the Government are noteworthy, especially the significant variables – including the consumer price index, which determines the inflation rate and growth of broad money supply. Investors are likely to be able to carry out prudent measures to avoid entering the stock market during high volatility, or to take advantage of fluctuations in price and make abnormal returns resulting from price spread. As findings from this study reveal, investor sentiment plays an important role in predicting the movement of KLCI, especially on a longer horizon of five months and beyond; investors may use this information to make decisions on appropriate strategies.

6.5 Limitations of the Study and Recommendations for Future Research

One of the major challenges in this study is the unavailability of a direct measurement for investor sentiment. Numerous studies have adopted the consumer confidence index as a reliable proxy. However, unlike other countries, data for the consumer sentiment index provided by the Malaysian Institute of Economic Research are not available in monthly frequency. As a result, the index is not appropriate as the sole reliable proxy for investor sentiment. In view of the unavailability of a direct proxy, this study proposes the construction of an investor sentiment index from a comprehensive number of indirect proxies available from the equity market, in addition to the interpolated quarterly consumer sentiment index. For future research, results could be more meaningful in the presence of a single direct proxy for investor sentiment for the stock market. However, not all economists recommend complete reliance on surveys, since they could be influenced by external factors affecting the answers of respondents, and thus providing biased results. This view is highlighted by Baker and Wurgler (2006) in their research, which is also the core reference paper for this study.

This study covers the period from 2000-2012, which includes the global financial crisis of 2008. The intention of this study is to focus on the global financial crisis, which is a recent phenomenon of volatility. It may be advantageous for future studies to include earlier episodes of crisis, such as the major Asian financial crisis of 1997. The study could be further extended to examine any interesting observations arising from both episodes. Future studies may also divide the data into sub-periods of high versus low volatility over the period of study. The context of this study is the Malaysian stock market. These findings may not be generalised to other stock markets in the world. However, they may be applicable to similar emerging stock markets that are also order-driven. It would be interesting to explore the differences or similarities with other emerging stock markets. Cross-country comparisons can be made on the level of volatility and the magnitude of influence of fundamental and non-fundamental factors on fluctuations.

This study employs several methodologies in order to determine the most parsimonious model in examining the magnitude and direction of relationships between variables. The models adopted in this study are the VAR, VECM, and ARDL model. The investor sentiment composite index in this study is constructed using factor analysis with the extraction of principal component analysis, which is also the methodology used by Baker and Wurgler (2006; 2007). Nevertheless, there could possibly be a more precise methodology with better results that may be implemented in future studies.

Finally, most of the data collected in this study are in monthly frequency, except for the consumer sentiment index. For quarterly basis, the data are interpolated to align with other series of variables. On the other hand, the volatility of KLCI may be computed as frequent as daily basis. It is suggested that the clustering of volatility could be clearer if the data are extracted in daily frequency so that the fluctuation of each price may be clearly observed. The issue here is that proxies for the investor sentiment composite index are only available on monthly basis. Therefore, in the future, researchers may attempt to construct or adopt proxies that are able to represent investor sentiment on a daily basis, so that they are consistent with the measurement of index volatility. By constructing a more parsimonious and robust index based on higher frequency, future research could be steered towards more meaningful results produced by researchers, scholars, and practitioners of the equity market.

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