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THE ROLES OF INVESTOR SENTIMENT IN MALAYSIAN STOCK MARKET

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ABSTRACT

The objective of this work is to offer an alternative theoretical perspective and modelling of local investor sentiment proxies in Malaysian stock market. In the theoretical part, two alternative theoretical perspectives in understanding sentiment are introduced, namely, the cognitive-affective theory of mind from neuroscience and the ABC model of the cognitive psychology. In modelling, we identify a combination of survey-based and market-based investor sentiment proxies, namely, the consumer sentiment index, the business condition index, and the stock futures index. The validity of the theory and model is then falsified with empirical analysis by examining the long- and short-run as well as stability relationships of the sentiment proxies on the aggregate stock market index returns using suitable econometric methods. The findings revealed that the proposed sentiment proxies are statistically significant in relations to the stock market returns in the long- and short-run with varying degree of persistency. However, the relations are not homogeneous across different size, industry groups, and market states which are in line with the existing behavioural finance views. In summary, this paper provides a new theoretical insights and empirical evidence on the roles of sentiment in Malaysian stock market that offers valuable academic, practical and policy implications.

Keywords: behavioural finance, behavioural risks, sentiment risk, affective bias, stock market

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INTRODUCTION

Behavioural finance paradigm advocates that various behavioural risks distort investor full rational decision making. This causes deviation on assets fundamental valuation and induces market inefficiency. Sentiment is one of important behavioural risks reflected in the stock market. Since its discovery in 1980s, a growing body of follow-up research has shown that sentiment influences investor, asset prices, and market behaviours. The role of investor sentiment on the stock market activity and return generating process is important, but remains theoretically vague and empirically disputable. In behavioural finance worldviews, understanding sentiment is important for theory, investment practice, and policy. In theory, sentiment cannot be ignored in the true risk assessment because market participants rely on heuristics and sentiment (Dow, 2011). In investment practice, behavioural risks have a role to play because the stock prices are much too variable than the fundamental (Akerlof & Shiller, 2009). In policy perspective, Alan Green remarks that failure to anticipate financial crisis is partly due to insufficient development to model changes in sentiment (Dow, 2011). As such, a theory of investor sentiment warrants further scrutiny to validate its theoretical foundations and to defend its empirical claims.

Understanding human behaviours is rooted in psychology domains. In psychology perspectives, Cooley (1909, as cited in Stets [2003]) defined sentiment as feeling raised by thought and intercourse with others minds. Sentiment is interconnected with cognition and decisions always involve some sentiment (Dow, 2011). In finance research, the word sentiment has been variously defined as an index expressing an opinion, irrational beliefs, erroneous beliefs, and investor opinions, on the expectation for future cash flows and investment risk (Solt & Statman, 1988; Morck, Shleifer, & Vishny, 1990; Barberis, Shleifer, & Vishny, 1998; Shefrin, 2008; Chang, Faff, & Hwang, 2012). The investor expectations on future market states could exhibit bullish (optimism) or bearish (pessimism). Meanwhile, investor reaction could be underreaction or overreaction to news (Barberis et al., 1998; Lee, Shleifer, & Thaler, 1991; Baker & Wurgler, 2006). Taken all these ideas together, sentiment risk could be regarded as systematic behavioural risk that affects security values through changes in expectations and risk aversion level (Murphy, 2012). To some extent, excessive sentiment risk will cause stock market instability (Dow, 2011).

Currently, the main gap in sentiment research is the absence of unified theory of investor sentiment that is able to explain both short- and long-term behaviours of investor sentiment (Burghardt, 2011). In this regards, theorizing works need to address on how to measure and quantify investor sentiment (Baker & Wurgler, 2007) and possibly this needs to relate to the theory of human behaviours (Dow, 2011). Guided by these suggestions, the current research is undertaken with the objectives to theorise and model local investor sentiment proxies in Malaysian stock market. We provide a new insight on the theoretical framework in modelling investor sentiment. The validity of the theory and model is then falsified with empirical analysis using suitable econometric methods. The results are in line with the behavioural finance view of significant and heterogeneity role of sentiments in the stock market.

THEORY AND EVIDENCE ON THE ROLES OF INVESTOR SENTIMENT

Theoretical Foundations

Existing theories, although not unified, offer theoretical underpinnings on the role of sentiment in financial markets. To recap, modern finance paradigm assumes that investors are rational in making decisions and should value investment in stocks, rationally (Lawrence, McCabe, & Prakash, 2007) based on the present value model of Gordon and Shapiro (1956) as presented by; $P = \sum_{t=1}^{n} \frac{CF_t}{(1+R)^t}$. In this equation, P is the current market price and, CF is the cash flow (future dividends) to be generated from investing in stocks. R is the discount rate that will influence the rate of growth of dividends.

In academic discourse, there are two perspectives in relating the role of sentiment to stock price formation through this model, namely by way of the rational and irrational role of sentiment. The rational role of sentiment in determining the prices formation is argued in Bos and Anderson (1988). In this perspective, the CF is a function of the firms' future profitability, which is directly related to the future demand for goods and services. The future demand is a function of future consumer behaviours that is a function of today consumer sentiment. Consumer sentiment measures how the consumer feels about the present and the future of consumer spending, business and economic conditions. Confidence is regarded as rational when people use information rationally to make prediction and decision (Akerlof & Shiller, 2009). This perspective hypothesises that there should be a high correlation between changes in consumer sentiment and changes in share prices (Bos & Anderson, 1988).

On the other hand, some present the irrational conceptualisation of sentiment role. In this sense, Baur, Quintero and Stevens (1996) incorporates the investor sentiment in setting market prices as in equation; $P = \frac{D}{R} + S$. This model suggested fundamental (D) and sentiment (S) as the two prime suspects in setting stock prices. Lawrence et al. (2007) explains the sentiment influence through the following model; $P = \dfrac{D}{r_s - g_s}$. Here, sentiment influences expectation on discount rate (r^s) and growth rate (g^s). This model postulates that high (low) sentiment is associated with low (high) expectation on *r* and higher (lower) expectation on *g*, making the stock value to be higher (lower). The role of sentiment as irrational is possible if investor processes the information irrationally that will induce irrational decisions (Akerlof & Shiller, 2009). In a more general framework, Majumder (2014) conceptualises sentiment as irrational forces in asset pricing for inefficient markets. This author models firm's stock returns determinants as a composition of two parts as; $R_t^E = R_t^F + R_t^{NF}$. One part is due to fundamental factors (R_t^F), and the other part is by non-fundamental factors (R_t^{NF}), which represents sentiment.

The above theoretical discussion does not provide a conclusive opinion and point to the dual roles of sentiments on asset pricing. As such, the above theory discussion is complemented with syntheses of the following existing theories to guide decisions on whether sentiment is to be regarded as rational or irrational elements in the asset pricing modelling. Bounded rational theory (Simon, 1955) and the animal spirits hypothesis (Keynes, 1937) explain why sentiment matters in human decisions. Bounded rational theory idealizes that investor decision is bounded rational due to interplay of cognitive and affective (Jones, 1999) or reasoning and intuition (Kahneman, 2003) elements in mind that make people's decision to be goal oriented and adaptive (Jones, 1999). Meanwhile, animal spirits hypothesis postulates that human action in uncertain environment will depend on a combination of rational calculation, conventional judgments and animal spirits (Akerlof & Shiller, 2009). In practice, the path of consumption following a shock to sentiment can point to either an animal spirit or an information view (Lachowska, 2011). The noise trader hypothesis (Kyle, 1985; Shleifer & Summers, 1990) explains who are the noise traders and how they affect the prices and market. Noise traders are irrational traders that trade based on noise (including sentiment) not fundamental information (Black, 1986; Shleifer & Summers, 1990). This will distort fair fundamental valuation, influence prices formation since noise traders are not fully offsetted by arbitrageurs, and will cause the market to be imperfectly rational (Black, 1986; Shleifer & Summers, 1990; Kalay & Wohl, 2009). Investor sentiment hypothesis (Baker & Wurgler, 2007) explains how and what stocks are prone to sentiment. This hypothesis postulates that, stocks that are speculative and difficult to value and arbitrage are expected to have a strong relationship with investor sentiment. On the other hand, safe and easy to arbitrage stocks are expected to have a weak relationship with sentiment. Finally, the confidence multiplier (Akerlof & Shiller, 2009) justifies why confidence is a suitable measure of sentiment. Confidence implies non-fully rational behaviours induced by affect state of an individual, others confidence, and others views of others confidence. Investor depends on confidence in investment decisions and confidence is associated with feeling right coming straight from the gut of which fundamental justification may or may not present.

All of the above theories are motivated from psychology, of which perspectives are limited in understanding human behaviours deviation from rationality assumption (Dow, 2011). Psychology perspectives are limited in the sense that behaviours are theorised in ex-post and they are collectively termed as animal spirits, irrational behaviours, and noise risks. These perspectives offer limited insights for modelling and policy design to minimise behavioural risks.

Empirical Evidence on Survey-Based Sentiment Measures

In brief, the existing empirical works on investor sentiment measures can be grouped into direct measures (survey-based), and indirect measures (market-based and media-based). The popular market-based measures are introduced by Baker and Wurgler (2006; 2007), and an example of the media-based is discussed in Tetlock (2007) and in Luo, Zhang and Duan (2013). Summary of measures of sentiment used in prior research is provided by Bandopadhyaya and Jones (2006). Recent research has also suggested local and global measures (Baker, Wurgler, & Yuan, 2012). We neglected bulk of these literatures and concentrated on the survey-based measures.

In the context of survey-based measures, earlier works by Branch (1985, as cited in Bos & Anderson, 1988) pointed that consumer sentiment as indicated by the consumer confidence index is a widely reported variable, which may prove valuable in security prices behaviours (Bos & Anderson, 1988). This is possible through the following forces. First, the consumer confidence indices are widely available in many countries (Zouaoui, Nouyrigat, & Beer, 2011) and regularly discussed in the press as an indicator of future economic prospects (Lachowska, 2011). Second, in investment practice, market participants rely on heuristics and market sentiment (Dow, 2011). Since then, many follow-up studies have been conducted on the same, but the roles of sentiment remained unclear. Just like inconclusiveness in theoretical grounds, the empirical evidences on the role of sentiment in the stock market are also mixed. The following forces, possibly explain this. First, it may be due to different proxies for sentiment used. Second, it may be due to various issues of heterogeneity, including difference in economic condition, market condition, sentiment states, investor group, company size, company salient, and industry group. We summarise these evidences in the following Tables 1 and 2 to conserve space. These issues need to be taken into consideration to derive economic and statistical meanings on the role of sentiment.

Table 1
Main studies using survey-based as sentiment indicators

Sentiment Indicators	Author	Market	Data	Models	Key Findings
▪ Index of Consumer Sentiment (*UM*) ▪ Consumer Confidence Index *(CB)*	Bos & Anderson (1988)	United States/ Stock market/	S&P 500 / 1967–1984	Regression / *Sentiment > changes in S&P prices*	▪ Strong positive relationship between consumer sentiments and S&P prices (R^2 = 0.95).
▪ Index of Consumer Sentiment (*UM*) ▪ Consumer Confidence Index *(CB)*	Fisher & Statman (2003)	United States/ Stock market	S&P 500 stocks, Small-Cap stocks, Nasdaq stocks/ 1978:02 – 2002:12	Regression/ *Consumer confidence > Investor sentiment index and Stock returns*	▪ All size groups stocks are affected by confidence. ▪ Positive relationship between consumer confidence and contemporaneous stock returns. ▪ Negative relationship between consumer confidence and future stock returns.
▪ The Consumer Confidence Indicator *(EC)*	Jansen & Nahuis (2003)	11 European Countries/ Stock markets	Respective countries' stock markets indices/ 1986–2001	Correlation and Causality/ *Confidence > Investor sentiment index and Stock returns*	▪ No long-run relationship between stock prices and consumer sentiment. ▪ In short run, stock returns Granger-cause consumer confidence in short horizons.
▪ Index of Consumer Sentiment (*UM*) ▪ Consumer Confidence Index *(CB)*	Lemmon & Portniaguina (2006)	United States/ Stock market	Smaller and larger size stocks portfolios/ 1956–2002	Regression/ *Sentiment > Stock returns*	▪ Investor sentiment forecast the returns of small stocks and stocks with low institutional ownership.

(*continued on next page*)

Table 1: (*continued*)

Sentiment Indicators	Author	Market	Data	Models	Key Findings
▪ The U.K. Consumer Confidence Indicator	Leger & Leone (2008)	United Kingdom/ Stock Market	240 U.K stocks/ 1985:01 – 2011:12	Principal Component Analysis and Regression/ *Sentiment*	▪ Consumer confidence could be a signal for the evolution of stock prices. ▪ Consumer confidence showed higher explanatory in the pre-bubble period.
▪ Index of Consumer Sentiment (*UM*)	Chen (2011)	United States/ Stock market	S&P 500 index/ 1978:01 – 2009:05	Markov-switching framework/ *Sentiment > Stock returns*	▪ Market pessimism has larger impacts on stock returns during bear market. ▪ Lack of confidence (negative sentiment) has an asymmetric effect on stock returns.
▪ Index of Consumer Sentiment (*UM*)	Akhtar, Faff, Oliver, & Subrahmanyam (2012)	United States / Stock and futures markets	DJIA, S&P 500, DJIA futures, and S&P 500 futures indices/ 1991:01–2010:08.	Regression *Sentiment > Stock returns*	▪ Bad sentiment news associated with negative market effect. While, good news, now market reaction. ▪ Negativity effect mostly salient stocks.
▪ Consumer Confidence Index *(CB)*	Antoniou, Doukas, & Subrahmanyam (2013)	United States/ Stock markets	Stocks from NYSE and AMEX exchanges/ 1967:02–2008:12	Regression *Sentiment > Momentum*	▪ Momentum profits arise only under optimism.
▪ Index of Consumer Sentiment (*UM*)	Casey & Owen (2013)	United States/ General economic	Various economic fundament al and the DJIA index. 1983:97 – 2008:07	Regression *Consumer Confidence > Economic fundamentals and DJIA index.*	▪ Positive and negative asymmetries in consumer reactions to economic fundamentals.

Note: UM = University of Michigan; CB = the Conference Board; EC = the European Commission

Table 2
Analysis of investors' sentiment heterogeneous effects on stock returns

Heterogeneous Determinants	Environment/Condition	Sentiment effects on returns		Studies
		Significant	*Degree of biasness*	
Economic condition	Recession	Yes/No	High	Chung, Hung, & Yeh (2012); Garcia (2013)
	Expansion	Yes	Low	
Market condition	Bear Market	Yes	High	Kurov (2010)
	Bull Market	Yes	Low	
Information states	Negative	Yes	High	Akhtar, Faff, Oliver, & Subrahmanyam (2011)
	Positive	Yes	Low	
Sentiment states	Pessimism	Yes	High	Stambaugh, Yu, & Yuan (2012)
	Optimism	Yes	Low	
Investor group	Retail	Yes	High	Lee et al. (1991);
	Institutional	Yes	Low	Kumar & Lee (2006); Schmeling (2007); Kling & Gao (2008)
Company size	Small	Yes	High	Baker & Wurgler
	Big	Yes	Low	(2006; 2007); Lemmon & Portniaguina (2006); Kaplanski & Levy (2010)
Company salient	High Salient	Yes	High	Akhtar et al. (2012)
	Low Salient	Yes	Low	
Industry group	Less stable industries	Yes	High	Kaplanski & Levy
	Stable industries	Yes	Low	(2010); Chou, Ho, & Ko (2012); Chen, Chen, & Lee (2013); Dash & Mahakud (2013)
Cultural traits	Collectivism	Yes	High	Statman (2008);
	Individualism	Yes	Low	Statman & Weng (2010)

Notes: Summary of the expectations about the effect of investors' sentiment according to the environment or conditions.

THEORISING AND MODELLING INVESTOR SENTIMENT IN MALAYSIA

Sentiment Risk in Emerging Financial Markets

Investors are paying attention to exploit the world's largest emerging financial markets because these markets are offering relatively higher returns compared to developed financial markets (Kearney, 2012). At the same time, behavioural finance researchers warned investors that the risk in emerging financial markets are affected by both fundamental and behavioural forces especially sentiment. The degree of behavioural risks biasness is expected to be higher in emerging financial markets through still significant in developed financial markets (see Ritter, 2003; Schmeling, 2009). This claim is supported by theoretical and empirical facts that people in emerging countries, especially in Asia suffer from behavioural biases with higher level than people of other cultures. In particular, Asian are more socially collective that provides psychological theoretical justification on close connection among the peoples and this leads to high tendency of reference to others in decision- making (Yates, Lee, & Bush, 1997; Kim & Nofsinger, 2008). The combination of fundamental and behavioural forces in decision-making makes the market players to be boundedly rational that directly causes the financial markets to be relatively less informationally efficient (Bekaert & Harvey, 2002).

The above facts provide justification for the importance of behavioural finance research in emerging financial markets. Malaysia is chosen as the testing case due to its representativeness of quite a developed capital market among the emerging countries (Mohamad, Hassan, & Ariff, 2007). Single country data is preferred to mitigate the country heterogeneous characteristic effect due to differences in economics, political, institutional, demographics and culture (Bekaert & Harvey, 2002; Statman, 2008; Kearney, 2012) that might limit the generalisation of the findings for emerging financial markets. Equally important the researchers' familiarity and knowledge on the Malaysia financial markets environment which is needed to conduct meaningful research (Bekaert & Harvey, 2002). In addition, evidence of bounded rationality and adaptive weak efficiency of the Malaysian stock market due to behavioural risks is discussed in Tuyon and Ahmad (2016). This research suggests details understanding of behavioural risks in this market is warranted.

Alternative Theoretical Perspectives

Since the seminal work of noise trader risk in financial markets by De Long, Shleifer, Summers and Waldmann (1990), growing empirical evidence have shown that sentiment is one of the sources of this risk. However, most of the research are empirical based and neglect the theoretical underpinning of investor sentiment. This causes varied definition of investor sentiment with no universally accepted measures of investor sentiment (Zouaoui et al., 2011) reflected in behavioural finance literature.

In this research, we propose an alternative theoretical framework that is believed to be able to draw the origin, causes, and consequences of investor sentiment. Idealised from interdisciplinary theories, this framework provides an understanding of the origin, cause, and effects of sentiment on market activity which has been earlier suggested in Tuyon and Ahmad (2014). The first theory is the neuroscience-based cognitive-affective theory of mind (Premack & Woodruff, 1978). Reference to this theory is justified from the perspective that human behaviour is a result of thinking that is originated from minds and body (Fast, Hertel, & Clark, 2014). This cognitive-affective theory of mind provides the basis for understanding the neural bases of the human mind through the two systems of brain namely cognitive and affective. Both of these systems induce biases collectively termed as cognitive heuristics and affective biases. Sentiment is one of the affective bias. The second theory is the cognitive psychology-based ABC model (Ellis, 1976). According to this model, the root cause of human behaviour irrationality (both by affective and cognitive) can be understood logically by this theory. According to this model, the C-*behavioural consequences* (positive or negative) arise from B-*core beliefs* or belief system (affect and cognitive which contains both rational and irrational elements) that are triggered by various A-*activating events* (Ellis 1976; 1991). A similar approach has been employed by Brahmana, Hooy and Ahmad (2012a; 2012b) in explaining the role of mood in stock market. Guided by these two theories, the origin, causes, and effects of sentiment can be theoretically justified as self-explanatorily as illustrated in the following Figure 1. The signs (+/–) denote favourable/(unfavourable) activating events that will induce positive/(negative) beliefs and behaviours accordingly.

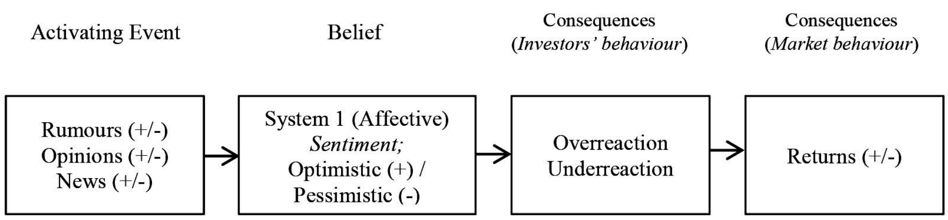

Figure 1. Conceptual framework for sentiment and stock returns theoretical relationships

The above framework also can be used to interprete the causal relation between sentiments and return generations. The state of the sentiment (i.e. optimism/neutral/pessimism) will induce trading behaviours (i.e. overreaction/

underreaction), which will influence changes in trading volume, volatility, prices and accordingly determine stock returns. Should sentiment affects the aggregate market returns, changes in sentiment should be positively related to contemporaneous stock market returns and negatively related to future stock market returns (Baker & Wurgler, 2006; 2007). Based on the above framework, the mathematical linear relationship between sentiment and returns can be written as in Equation 1 as presented in Schmeling (2009).

$$R_{i,t} = \alpha + \beta SENT + e_t \qquad (1)$$

Modelling Investor Sentiment

The modelling of investor sentiment involves two processes, namely defining sentiment and measuring the sentiment effect via testable hypotheses. The definition and possible proxies of sentiment are as illustrated in Figure 1, whereby sentiment is affective bias in System 1 of the human minds. This feeling is activated by activating events like rumours, opinions and news. The idea is to find possible proxies that represents these activating events that are possibly influencing investor's affective mind in the stock market investing.

In measuring investor sentiment, this research proposes a new construct of investor sentiment proxies in the Malaysian stock market based on the consumer sentiment index (SC), business condition survey (SB) and stock futures index (SF). The justifications are briefly elaborated here. These variables have high possibility to influence investor thinking and decisions. These sentiment proxies represent the opinions from consumers, business owners, and institutional investors. SC has been widely used as a direct measure for investor sentiments that are widely documented in general and financial press (Corredor, Ferrer, & Santamaria, 2015) globally. Intuitively, opinion reflected in consumer confidence index could be referred by investors to gauge the likelihood of future stock market performance (Lemmon & Portniaguina, 2006; Chen, 2011). Use of SC as a significant direct measure of investor sentiment indicator influencing stock returns has been established in the literature (see evidences in Table 1). Similarly, the SB is a survey of business owners' opinions that could be used as a direct measure of investor sentiment but has been relatively neglected in the literature. In Malaysia, the Malaysian Institute of Economic Research (MIER) publishes both SC and SB on a quarterly basis since 1987. The SC is an opinion drawn from consumer perspective about the economy prospects and future spending expectations. SB represents an opinion from firms about the economic and future business prospects. The SC and SB have also been used by Mat Nor, Ibrahim and Rashid (2013), Mat Nor, Rashid, Ibrahim and Yunyi (2014), and Rashid, Hassan and Yein (2014) as a measure of investor sentiment in Malaysia. The third variable for sentiment proxy is stock futures index. The lead-lag hypothesis postulates that futures index leads the cash index future performance (Brooks, Rew, & Ritson, 2001). Thus, trading in futures market represents an investors' opinion about future cash market conditions. Brooks et al. (2001) provided two-market practice reasons for the association of these two indices. First, sentiment and arbitrage trading cause these markets to be correlated. Second, the professional trader's conventional wisdom suggests that movements in the futures market should reflect the expected future movements in the cash market. Based on these justifications, stock futures index could provide a sentiment indicator for changes in stock prices in the cash market. This claims is in line with Safa and Maroney (2012).

The following testable hypotheses regarding the relationships between investor sentiment and the stock market are drawn from the proposed theoretical framework and the existing behavioural finance literature as discussed herein. First, investor sentiment influences the stock returns. The behavioural finance postulates that the effect of investor irrational sentiment waves is measured by overly optimistic or pessimistic expectations on stock returns using aggregate stock market index (Schmeling, 2009; Kurov, 2010) or portfolio of individual stocks (Baker & Wurgler, 2006; 2007). The theoretical argument for sentiment stock market relationships is presented in Baker and Wurgler (2007). In addition, since affect is a permanent feature in the human minds as discussed in the theoretical part, we argue that sentiment is to be persistently reflected in the stock markets. This notion is in line with claim by Zouaoui et al. (2011). Accordingly, Hypothesis 1 is drawn as follow:

> H1: Investor sentiment influences the aggregate stock market returns. The influence of investor sentiment on the stock market returns is expected to be pronounced both in the long- and short-run. In addition, the relationships are expected to be stable over time, indicating a persistent influence.

Second, the degree of investor sentiment influences on the stock market returns is heterogeneous due to various conditions. It has been empirically established that there is a difference in the degree of influence of investor sentiment on stock returns in different firm size and industry type. For firm size, Baker and Wurgler (2006; 2007) suggested that sentiment risk is more vulnerable to stock that are speculative and difficult to value and arbitrage (i.e. newer, smaller, more volatile, distressed, extreme growth) compared to safe and easy to arbitrage stocks (i.e. regulated utilities, firm with long earning history, stable dividend). However, Statman, Fisher and Anginer (2008) noted that investor higher attention to popular companies may play an influencing demand for these stocks. In this regard, sentiment could also influence big size firms (Akhtar et al., 2012). As for industry type, recent research provides evidences that firms in different industries are reported to have different sentiment effect (Kaplanski & Levy, 2010; Chou et al. 2012; Chen et al., 2013; Dash & Mahakud, 2013). The behavioural explanation to this issue is discussed in data description and segmentation section. In this regard, Hypothesis 2 is set as follow:

> H2: Investor sentiment influence on the aggregate stock market returns is heterogeneous on the condition of firm size and industry type. In this research, firm size refers to stock index that represents the big and small capitalised firms. While industry type refers to defensive and cyclical industry stock market index.

DATA AND ECONOMETRIC METHODS

Data Description and Segmentation

In this paper, we look at different proxies of investor sentiments drawn from business surveys, consumer surveys, and derivative market indicator. Due to availability and standardisation of data, the period of the series is limited from January 1996 to December 2014. Data for SC and SB are obtained from MIER, while the rest is obtained from Bloomberg. The original data for SC and SB are in quarterly data and transformed to monthly data for consistency of the frequency of data using interpolation method.[1] As for the stock data, we use various aggregate indices data. Returns are calculated as $R_t^{I,i} = \log\left(\frac{P_t}{P_{t-1}}\right)*100$

We segmented the stock market indices into respective size and industry groups. Index size classification is based on the definition used by Baker and Wurgler (2007). Industry type is classified in two groups as being either defensive or cyclical (Dirks, 1958; Becher, Jensen, & Mercer, 2008; Held, 2009; Nagy & Ruban, 2011). Firms in a different industry are expected to have a different characteristic. Specifically, defensive industry is expected to be less sensitive to macroeconomic and market fluctuations. On the other hand, the cyclical industry is more sensitive to the macroeconomic and market developments (Becher et al., 2008; Held, 2009; Nagy & Ruban, 2011). Size-based; (i) speculative firms (BM70, BM Small Cap, and BM Fledgling) which are characterised as small-capitalised firms, speculative in nature, and volatile earnings, lower prices, and extreme growth. (ii) stable firms (BM KLCI, BM100, and BM Emas) which are characterised as large capitalised firms, and higher prices. Industry-based;[2] (i) cyclical (Mining, Property, Finance, and Construction) which are more sensitive to the macroeconomic and market developments and higher correlation with the market. (ii) defensive (Consumer, Plantation, and Trade & Services) which are expected to be less sensitive to macroeconomic and market fluctuations and correlation with the market is low. In the tests, two control variables are employed, namely, past returns and the crisis dummy. The pre-determined crisis market states[3] are; Asian financial crisis (28/02/97 to 1/09/98), the 911 attack and Technology slump (09/04/01 to 23/04/02), the SARS (23/04/02 to 11/03/03), and Subprime crisis (11/01/08 to 17/10/08).

To gauge the variable relationships, we draw the following Figure 2. It presents the pictorial outlook on the relationship between the stock market indices to the proposed three sentiment proxies. This portrays that these variables have been moving in the same pattern throughout the years and similar downward spikes are noted during the crisis market states mentioned above. In what follows, different from the previous studies, we examine the possible long and short-run as well as the stability of relationships of these three sentiment proxies in relation to the 13 indices in Malaysian stock market. This is performed to validate their economic and statistical relationships.

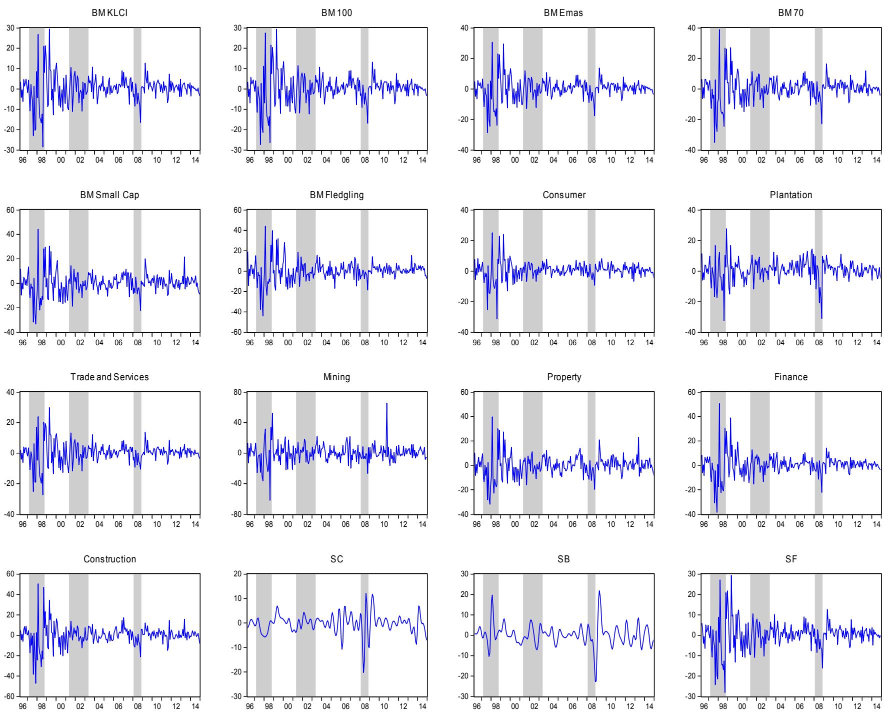

Figure 2. The time series plot of the 13 aggregate stock market index returns (first 13 graphs) and 3 sentiment proxies changes (last 3 graphs). The dashed areas are the crisis events.

Empirical Model and Econometric Methods

The empirical model for sentiment-return relations is set according to the following autoregressive process of order 1 framework. Where, the respective stock index returns ($R_t^{I,i}$) is partly explained by three sentiment proxies namely the MIER's consumer sentiment index (SC_t), the MIER's business condition index (SB_t), and stock futures index (SF_t). The lag one return is included as control variable that explains returns and crisis dummy (D) is used to capture the crisis effects, while ε_t represents the standard error term. In line with the identified hypotheses, we statistically examine the investor sentiment and the stock index returns relationships; i.e. (i) cointegration, (ii) long-run equilibrating relationships, (iii) short-run dynamics, and (iv) stability of relationships.

$$R_t^{I,i} = f(R_{t-1}^{I,i}, SC_t, SB_t, SF_t, D) \tag{1}$$

The Autoregressive-Distributed Lag (ARDL) regression model developed and advanced by Pesaran and Shin (1998), and Pesaran, Shin and Smith (2001) is used to examine the nature of long- and short-run relationships between the sentiment variables and the stock index returns. The ARDL model is suitable to be employed in the analysis due to the following advantages. First, this model has been tested to be more efficient in cointegration test with unrestrictive assumptions about the variable order of integration unlike the typical cointegration test. This method can be applied to test a long-run level relationships among the dependent variable and the regressors irrespective whether the regressors are $I(0)$ and/or $I(1)$, but none with $I(2)$ (Pesaran et al., 2001). Menkhoff and Rebitzky (2008) has used this method in modelling level relationships of sentiment in the US-dollar for all $I(1)$ variables. While Rushdi, Kim and Silvapulle (2012) has used ARDL for mixed order of intergation, $I(0)$ and $I(1)$. Second, this method can be used to examine both long- and short-run relationships in a single equation approach (Pesaran et al., 2001). The basic form of ARDL model is as follow;

$$\begin{aligned}\Delta R_t^{I,i} &= \alpha_0 + \sum\nolimits_{i=1}^{n} \beta_1 \Delta R_{t-P}^{I,i} + \sum\nolimits_{i=0}^{n} \beta_2 \Delta SG_{t-q} + \sum\nolimits_{i=0}^{n} \beta_3 \Delta SB_{t-q} + \\ &\sum\nolimits_{i=0}^{n} \beta_4 \Delta SF_{t-q} + \gamma_1 R_{t-1}^{I,i} + \gamma_2 SC_{t-1} + \gamma_3 SB_{t-1} + \gamma_4 SF_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

where, $R_t^{I,i}$ is the dependent variable, $R_{t-1}^{I}, SC_t, SB_t, SF_t$ are the explanatory variables, and ε_t is a random error term. The autoregressive component is represented by $R_{t-p}^{I,i}$ where lag value of dependent variable partly explains itself. The successive lags of explanatory variable, $SC_{t-q}, SB_{t-q}, SF_{t-q}$

represent the distributed lag component in the model. The optimal *p* and *q* lags are determined using information criteria (AIC) for standardise lags (*p, p*). Analyses are performed based on the following steps.

In the first step, the evidence of cointegration is examined through the ARDL Bound test. The objective is to determine if there exists a long-run cointegration among variables. This is conducted by imposing restrictions on the estimated long-run coefficients of relevant variables R^I_{t-1}, SC, SB, SF for all indices (13 models). The null hypothesis of no cointegration (no long-run relationship) among the variables is $H_0: \gamma_1 = \gamma_1 = \gamma_1 = \gamma_1 = 0$ which is testing the joint coefficient of the lagged level variables in the ARDL model. The Wald statistic is used to determine the cointegration significant at the standard conventional level. In the second step, we examine the long run relationship between dependent and independent variables. The long-run effects are extracted from the unrestricted error correction model (ECM) of the above model. The inspected long-run equilibrium coefficients are; $\Delta R_t = 0,\ \Delta R_{t-1} = 0,\ \Delta SC = 0,\ \Delta SB = 0,\ \Delta SF = 0$

In the third step, short-run relationship is inspected using the following error correction mechanism (ECM) version of modified ARDL. All this will be done using the ECM applied through the Ordinary Least Square (OLS) method. The error-correction term (ECT) is the OLS residuals series from the long-run cointegrating regression. A significant negative ECT coefficient indicates existence of short-run dynamics.

$$\Delta R^{I,i}_t = \alpha_0 + \sum\nolimits_{i=1}^{P_1} \gamma_1 \Delta R^{I,i}_{t-i} + \sum\nolimits_{i=0}^{q_1} \gamma_2 \Delta SG_{t-1} + \sum\nolimits_{i=0}^{q_2} \gamma_3 \Delta SB_{t-i} + \sum\nolimits_{i=0}^{q_3} \gamma_4 \Delta SF_{t-i} + \gamma_5 ECT_{t-1} + \varepsilon_t \qquad (3)$$

Finally, the stability of sentiment-returns relationships is analysed using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares recursive residuals (CUSUMSQ) methods pioneered by Brown, Durbin and Evans (1975). The CUSUM test detects systematic changes in the regression coefficients, while the CUSUMSQ detects sudden departures from the constancy of regression coefficients (Yin & Hamori, 2011). The calculation for CUSUM (W_r) and CUSUMSQ (S_r) are as in Equation 4 (Bos, Ding, & Fetherston, 1998). The null hypothesis of constancy of variables relationships over time is examined by detecting differences among β_S; H_0, $\beta_1 = \beta_2 = ... = \beta_t = \beta$; or through variance of changes; H_0, $\sigma^2_1 = \sigma^2_2 = ... = \sigma^2_t = \sigma^2$ (Brown et al., 1975) with standard significance level (Bos et al., 1998).

$$W_r = \sum_{t-1}^{r} W_t \text{ and } S_r = \frac{\sum_{t-1}^{r} W_t^2}{\sum_{t-1}^{n} W_t^2} \tag{4}$$

FINDINGS AND DISCUSSIONS

The descriptive statistics are as reported in Table 3. The statistical requirements for the use of ARDL, namely, the order of integration and serial independence are fulfilled but not for the dynamically stable characteristics for all models. The variable order of integration is inspected using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. We inspected variables series at level and first difference with intercepts only. The results as presented in Table 4, confirmed that all variable order of integration are $I(0)$ with 1% significant level except for SC and SB which is significant at the 5% level, and none of the variables are of $I(2)$. Note that the data is not normal but this can be ignored as the central theorem is assumed in large samples (> 30 or 40) (see for example Ghasemi and Zahediasl, 2012).

In the ARDL cointegration analysis, we first started with performing the ARDL Bound test. We opt to perform the Bound test within no intercepts and no trends.[4] In this test, we need to ensure that serial correlation problem does not exists in all models. The optimal lag for all the models are as suggested by AIC. The results for Bound tests for all models are presented in Table 5. Based on the results, evidence for cointegrated variables can be established only for big firm and defensive industry groups and not for other groups. This is in contrast to the general belief that only small and speculative industries are sensitive to sentiment risks. Also note that, the sentiment proxies together with the control variables explain more than 50% of the respective stock market index returns. This indicates the importance of these variables to the stock market performance in Malaysia.

Second, the long-run relationships between sentiment and returns are examined and the results are as summarised in Table 6. The results indicate that the sentiment proxies do significantly influence the stock market returns of all index segments in the long-run as theoretically expected. However, the effect of sentiment is heterogeneous and is more pronounced for big firms and cyclical industry. Also note that, SC and SB have higher relations with returns compared to SF. These results provide support to the validity of H1 and H2.

Table 3
Summary of descriptive statistics

Segmentation	Indices	Mean	Median	Max.	Min.	S.D.	Skewness	Kurtosis	JB-Stats	Prob.
Big Firms	BMKLCI	0.19	0.87	29.44	–28.46	6.85	–0.07	7.3	173.48	0
	BM100	0.21	0.69	29.4	–27.33	7.03	–0.12	7.03	153.1	0
	BMEmas	0.15	0.69	30.73	–28.61	7.23	–0.04	7.33	175.57	0
Small Firms	BM70	0.11	0.62	38.97	–35	8.15	–0.02	7.93	227.96	0
	BMSC	–0.05	0.15	44.19	–33.36	9.22	0.37	7.04	158.25	0
	BMFL	–0.03	0.24	44.05	–44.11	9.94	0.23	8.15	250.51	0
Defensive Industry	CSU	0.4	0.74	25.06	–31.33	5.7	–0.54	11.31	658.44	0
	PLN	0.47	0.97	27.75	–32.43	7.09	–0.82	7.07	180.66	0
	SER	0.1	0.6	29.76	–27.31	7.08	–0.08	6.43	110.63	0
Cyclical Industry	TIN	0.02	–0.18	65.52	–61.78	12.33	0.32	9.87	446.17	0
	PRP	–0.28	0.09	39.69	–31.93	8.93	0.3	6.37	109.71	0
	FIN	0.62	0.84	50.59	–38.55	8.91	0.52	10.97	606.13	0
	CON	–0.22	0.36	50.55	–47.19	10.25	0.18	9.84	439.37	0
Sentiment	SC	–0.2	0.15	12.14	–20.25	3.94	–0.79	7.48	211.19	0
	SB	0.21	0.18	21.9	–22.74	5.31	0.2	8.22	256.67	0
	SF	0.23	0.73	29.38	–28.08	6.86	–0.12	7.42	184.05	0

Notes: Classification of FTSE-Bursa Malaysia; BMKLCI, BM100, and BMEmas comprises of large capitalised firms. BM70, BMSC (BM Small Cap), and BMFL (BM Fledgling) represents small capitalised listed firms. The industrial indices are; CSU (Consumer), PLN (Plantation), SER (Trading and Services), TIN (Mining), PRP (Properties), FIN (Finance), CON (Construction). Number of observation are equal to 255 for all.

Table 4
Unit root tests

Variables/ Methods	ADF			PP		
	Level	1st Difference	*I*(d)	Level	1st Difference	*I*(d)
Dependent Variable						
BM KLCI	–12.4109***	–9.9784***	*I*(0)	–12.3574***	–89.8705***	*I*(0)
BM 100	–12.5723***	–9.9718***	*I*(0)	–12.5609***	–94.2659***	*I*(0)
BM Emas	–12.5480***	–12.6099***	*I*(0)	–12.5319***	–91.9690***	*I*(0)
BM 70	–4.3763***	–6.6749***	*I*(0)	–12.5711***	–101.9091***	*I*(0)
BM Small Cap	–12.8356***	–6.7926***	*I*(0)	–12.8819***	–88.9186***	*I*(0)
BM Fledgling	–12.8623***	–7.1578***	*I*(0)	–12.8727***	–94.3117***	*I*(0)
Consumer	–13.5270***	–11.6626***	*I*(0)	–13.5395***	–105.8947***	*I*(0)
Plantation	–13.1943***	–10.8257***	*I*(0)	–13.1950***	–132.3065***	*I*(0)
Trade and Services	–12.7249***	–10.3903***	*I*(0)	–12.6483***	–96.9045***	*I*(0)
Mining	–14.8118***	–10.4836***	*I*(0)	–14.8227***	–161.8023***	*I*(0)
Property	–12.4233***	–12.2707***	*I*(0)	–12.4233***	–109.8068***	*I*(0)
Finance	–12.6739***	–12.9895***	*I*(0)	–12.7293***	–89.7915***	*I*(0)
Construction	–4.2723***	–6.3559***	*I*(0)	–13.8604***	–115.6271***	*I*(0)
Regressors Variable						
SC	–4.8172***	–11.2421***	*I*(0)	–3.4237**	–6.5421***	*I*(0)
SB	–6.7740***	–8.8458***	*I*(0)	–3.0221**	–4.3997***	*I*(0)
SF	–12.5095***	–12.4457***	*I*(0)	–12.4646***	–88.8456***	*I*(0)

Notes: The figures represent the *t*-Statistics. *I*(d) is the variable order of integration. The null hypothesis for both ADF and PP test is that the time series contains a unit root (non-stationary). *, **, and *** indicate 10%, 5%, and 1% level of significance respectively based on *p*-value.

Table 5
Summary of ARDL Bound test for cointegrating regression

Segmentation	Optimum lags	Coefficients							Wald Test
		$\bar{R}^2$	C	R_t	SC_t	SB_t	SF_t	D	
Big/ stable firms									
BM KLCI	(1, 0, 2, 4)	.53	1.386 (***)	–3.627 (***)	.661 (***)	.284 (***)	2.169	–4.209 (***)	6.178 (**)
BM100	(0, 0, 2, 2)	.52	1.323 (***)	–1.729 (***)	.671 (***)	.306 (***)	.414	–3.957 (***)	2.574
BM Emas	(4, 0, 1, 4)	.53	1.434 (***)	.634	.562 (***)	.330 (***)	–2.15 (**)	–4.365 (***)	7.336 (***)
Small/ speculative firms									
BM70	(3, 1, 1, 1)	.52	1.246 (**)	– .908 (***)	.553 (**)	.201	– .299	–4.232 (***)	3.106 (*)
BM Small Cap	(3, 2, 1, 1)	.52	1.114 (*)	– .982 (***)	.699 (**)	.378 (**)	– .295	–4.417 (***)	.477
BM Fledgling	(0, 2, 1, 2)	.50	1.013	– .906 (***)	.619 (**)	.375 (*)	– .311	–4.113 (**)	.541
Defensive industry									
Consumer	(1, 2, 1, 2)	.56	1.140	– .864 (***)	.895 (***)	.177	– .312	–4.611 (***)	20.539 (***)
Plantation	(0, 0, 2, 4)	.52	1.367 (**)	– 1.040 (***)	.542 (**)	.187 (*)	– .239	–3.212 (***)	6.231 (**)
Trade & Services	(0, 0, 1, 2)	.52	1.204 (**)	–1.299 (***)	.510 (**)	.278 (***)	– .046	–4.115 (***)	7.631 (***)
Cyclical industry									
Mining	(0, 0, 1, 4)	.57	1.302	–1.167 (***)	.952 (**)	.435 (**)	– .556 (*)	–4.718 (**)	.8074
Property	(1, 2, 1, 2)	.51	1.017	– .996 (***)	.811 (***)	.318 (*)	– .269	–4.769 (***)	.2403
Finance	(0, 2, 1, 2)	.54	1.592 (**)	– .667 (***)	.727 (***)	.407 (**)	– .795 (***)	–4.983 (***)	1.498
Construction	(1, 2, 1, 2)	.56	1.140	– .865 (***)	.896 (***)	.178	– .505	–4.612 (***)	.85013

Notes: *, **, and *** below the respective coefficients indicate 10%, 5%, and 1% level of significance respectively based on *p*-value. Diagnostic Checks for Serial correlation, RESET test, Normality, and ARCH test have been performed and all are in order except for normality as mentioned in the text. Optimal lags as determined by AIC.

Table 6
Summary of long-run relationships

Segmentation	Optimum lags	Coefficients					
		C	R_{t-1}	SC_{t-1}	SB_{t-1}	SF_{t-1}	D_t
Big/stable firms							
BM KLCI	(1, 0, 2, 4)	–1.3073	3.4205 (*)	– .6229	– .2673	–2.046 (**)	3.9700
BM 100	(0, 0, 2, 2)	1.323 (***)	– 1.7279 (***)	0.6707 (***)	.3065 (***)	.4149	– 3.9573 (***)
BM Emas	(4, 0, 1, 4)	.2252 (**)	.09961	.0884 (*)	.0518 (**)	– .3369 (***)	– .6855 (**)
Small/speculative firms							
BM 70	(3, 1, 1, 1)	1.1805	– .8069	.5243	.1909	– .2731	–4.0104 (*)
BM Small Cap	(3, 2, 1, 1)	1.4446	–1.2737	.9068	.4908	– .3829	–5.7289 (*)
BM Fledgling	(0, 2, 1, 2)	1.0137	– .9067 (***)	.6194 (**)	.3757 (*)	– .3119	–4.1134 (**)
Defensive industry							
Consumer	(0, 4, 1, 1)	1.1534 (***)	–1.2591 (***)	.2543	– .0686	.1981	–2.7112 (***)
Plantation	(0, 0, 2, 4)	1.3679 (**)	–1.0490 (***)	.5421 (**)	.1875 (*)	.2396	–3.2128 (***)
Trade & Services	(0, 0, 1, 2)	1.2042 (**)	–1.2999 (***)	.5101 (**)	.2784 (***)	– .0466	–4.1155 (***)
Cyclical industry							
Mining	(0, 0, 1, 4)	1.3024	–1.1676 (***)	.9521 (**)	.4354 (**)	– .5567 (*)	–4.7186 (**)
Property	(1, 2, 1, 2)	1.2318	–1.2058 (***)	.9821 (***)	.3857 (*)	– .3256	–5.7739 (***)
Finance	(0, 2, 1, 2)	1.5919 (**)	– .6666 (***)	.7272 (***)	.4075 (**)	– .7953 (**)	–4.9582 (***)
Construction	(1, 2, 1, 2)	.9201	– .6976 (***)	.7227 (***)	.1434	– .4704 (*)	–3.7207 (**)

Notes: *, **, and *** indicates 10%, 5%, and 1% level of significance respectively based on *p*-value. Optimal lags as determined by AIC.

Third, the short-run relationships among variables are statistically investigated and the results are as summarised in Table 7. The results are in confirmatory to the long-run results, where, in the short-run, sentiments are also affecting all segments of market index with more pronounced effect for big firms and cyclical industry. The higher influence of SC and SB on stock market returns are also maintained in the short-run. The significant negative ECT coefficient confirmed the existence of short-run dynamics. These results confirmed the theoretical short-run roles of the sentiments in relation to stock market returns. Collectively, these evidences also provide support to H1 and H2.

In the final analysis, the stability of relationships among variables is scrutinised. The analysis is extended to examine the stability of sentiment risk influences across times. Financial instability hypothesis postulates that if sentiment drives markets, it may cause market instability (Dow, 2011). This can be corroborated with the notion that non-economic motivations cause the ups and downs of the economic behaviours (Akerlof & Shiller, 2009). This instability and inefficiency although short lived, will persist consistently in the market so long as normal people are trading in the market (Slezak, 2003) because they regularly produce financial fads, euphoria and gloom (Sanford, 1994) in financial markets.

The results of CUSUM and CUSUMSQ tests are self-explanatory, and summarised in Table 8 (refer Appendix). The objective of the test is to examine the constancy of the regression coefficients of all explanatory variables to stock market returns. These stability tests seem to indicate the sentiment proxies with two control variables are persistent in relation to stock market returns. However, sentiments-returns relationship is noted to be more persistent for small firms and cyclical industry. For big firms and defensive industry, sentiment influence is moderately persistent. These results also provide support to the persistency and heterogeneity roles of sentiment as drawn in H1 and H2.

We synthesise the current research findings to existing behavioural finance empirical evidence. The unified theoretical underpinning for sentiment risks is still missing. Accordingly, this paper provides alternative theoretical perspectives borrowed from neuroscience (i.e. cognitive-affective theory of mind) and cognitive psychology (i.e. the ABC model) to understand sentiment risk. Specifically, cognitive-affective theory facilitates understanding of the origin of sentiment risk that is rooted in normal human minds. Whereas, the ABC model provides theoretical framework to interpret sentiment-returns relations. Both of these theories provide a theoretical base in understanding investor sentiment risk. This is motivated by the sentiment research gaps suggested by some scholars (Baker & Wurgler, 2007; Burghardt, 2011; Dow, 2011).

Table 7
Summary of short-run relationships

Segmentation	Optimum lags	Coefficients						
		ΔC	ΔR_{t-1}	ΔSC_{t-1}	ΔSB_{t-1}	ΔSF_{t-1}	ΔD_t	ECT_{t-1}
Big/stable firms								
BM KLCI	(1, 0, 2, 4)	1.3862 (***)	–3.6270 (**)	.6605 (**)	.2835 (***)	2.1699	–4.209 (***)	1.060
BM 100	(0, 0, 2, 2)	1.3237 (**)	–1.7297 (***)	.6707 (***)	.3065 (***)	.41490	–3.957 (***)	–1.000
BM Emas	(4, 0, 1, 4)	1.4341 (***)	.63434	.5629 (***)	.3304 (***)	–2.1459 (**)	–4.365 (***)	–6.37 (***)
Small/speculative firms								
BM 70	(3, 1, 1, 1)	1.246 (**)	–.9087 (***)	.5534 (**)	.2015	–.2883	–4.232 (***)	–1.055 (**)
BM Small Cap	(3, 2, 1, 1)	1.114 (*)	–.9821 (***)	.6992 (***)	.3784 (**)	–.2953	–4.417 (***)	–.771 (**)
BM Fledgling	(0, 2, 1, 2)	1.0137	–.9067 (***)	.6194 (**)	.3757 (**)	–.3119	–4.113 (**)	–1.000
Defensive industry								
Consumer	(0, 4, 1, 1)	1.1534 (***)	–1.2591 (***)	.25432	– .06860	.19810	– 2.7112 (***)	–1.000
Plantation	(0, 0, 2, 4)	1.367 (**)	–1.040 (***)	.5421 (**)	.1875 (*)	–.2396	–3.212 (***)	–1.000
Trade & Services	(0, 0, 1, 2)	1.204 (**)	–1.299 (***)	.5101 (**)	.2784 (***)	–.0466	–4.115 (***)	–1.000
Cyclical industry								
Mining	(0, 0, 1, 4)	1.302	–1.167 (**)	.9521 (**)	.4354 (**)	–.5567 (*)	–4.718 (**)	–1.000
Property	(1, 2, 1, 2)	1.017	–.996 (***)	.8112 (**)	.3186 (*)	–.2690	–4.769 (***)	–.826 (***)
Finance	(0, 2, 1, 2)	1.591 (**)	–.666 (***)	.7272 (***)	.4075 (**)	–.7953 (***)	–4.982 (***)	–1.000
Construction	(1, 2, 1, 2)	1.1404	–.864 (***)	.8957 (***)	.1777	–.5050	–4.611 (***)	–1.23 (***)

Notes: *, **, and *** indicates 10%, 5%, and 1% level of significance respectively based on *p*-value. Optimal lags as determined by AIC.

To date, there is no conclusive evidence on the influence of sentiment to stock returns of firms with different size (i.e. big and small firms). Earlier theoretical and empirical evidence provides support to higher influence of sentiment on small firm's stock returns due to higher concentration of retail investors, which are believed to be less rational (Baker & Wurgler; 2006; 2007;

Lemmon & Portniaguina, 2006; Kaplanski & Levy, 2010). However, recently some scholars have highlighted that big firm stocks are also subjected to sentiment risk due to their popularity that make them always in the spotlight of investors' attention (Statman et al., 2008; Akhtar et al., 2012). We confirmed the significant influence of sentiment risk to big firms.

Similarly, the different influence of sentiment on stock returns of firm in a different industry group has been recently highlighted. Specifically, firm's stock in a less stable industries is more affected by sentiment risks compared to a firm in a stable industry. This is justified by the fact that less stable industry stocks are more speculative in nature (Kaplanski & Levy, 2010) that make them possibly attractive to retail investors. We extend this line of inquiry by comparing the effects of sentiment risks on defensive (stable) and cyclical (less stable) industries.

Generally, the findings highlighted that sentiment risks influence all stock prices regardless of size and industry groups. This can relate back to the evidence that Malaysian investors, being in a collectivism society, are affected by sentiment in their investment decision making (Statman, 2008; Statman & Weng, 2010). In contrast to Western evidence, this finding indicates that both retail and institutional investors are influenced by sentiment waves. However, stability tests suggest that sentiment-returns relations are stable for firms that are small in size and those in cycle industries which is in line with existing beliefs. Whereas, the stability test for big firms and defensive industries are moderately stable. Stable relationships could indicate that the effect of sentiment is strong and moderately stable indicates the sentiment influence is relatively moderate.

CONCLUSIONS AND IMPLICATIONS

To recap, this research aims to theorise and model local investor sentiment proxies in the Malaysian stock market. We offer cognitive-affective theory (a neuroscience-based theory) and ABC model (a cognitive psychology-based theory) to explain the theoretical roles of sentiment in the stock market investment. In modelling, we conceptualise an influential sentiment proxy, namely SC, SB and SF which are reflected and attended in Malaysian the stock market daily, but their roles in inducing investor decisions have been taken for granted. This extends the works of Mat Nor et al. (2013; 2014) and Rashid et al. (2014) which have proposed SC and SB as suitable investor sentiment proxies in Malaysia. Statistical analyses are performed to examine the long-run, short-run, and stability of relationships of these three sentiment proxies to the 13 aggregate stock market indices that are segmented into size and industry groups.

The current research casts new insights on sentiment literature in the following ways. Firstly, it illustrates the origin, cause, and effect of sentiment as irrational forces originated from human minds. Secondly, in empirical analysis, we examine the long- and short-run relationships of sentiment proxies on various categories of aggregate stock market indices to acknowledge heterogeneity roles of sentiment based on different firm size and industry group. In the final analysis, we draw inferences on the stability of the sentiment-returns relationships across times, size, and industry group. Evidence from the current works challenge the general belief that sentiment forces are temporary in nature, only attract retail investors and expected to be more pronounced for small size firms and cyclical industries. Our analysis provides evidence of broad-based heterogeneous effects of sentiment in Malaysian stock market. Thirdly, this study provides new evidence to sentiment literature on the long-run, short-run, and stability roles of sentiments in influencing stock market returns particularly in Malaysia. Specifically, sentiments are more pronounced in big firms and cyclical industry, both in the long- and short-run. In terms of sentiment-returns relations' stability, relationships are generally persistent with higher persistence for small firms and cyclical industry, but moderately persistence for big firms and defensive industry. Finally, this study provides evidence that SC, SB, and SF are the possible direct measures of investor sentiment in Malaysia stock market.

Findings drawn in this paper provide valuable insights to academic, investment practices, and policy makers. They offer new perspectives on the current debate of whether sentiment should be regarded as rational or irrational, long- and short-term effects, permanent or temporary effects, homogeneous or heterogeneous effects, and whether sentiment matters for modelling asset pricing, investment analysis, and market efficiency policy. The results of this research provide support for the significant importance of sentiment risk in influencing the stock market returns economically and statistically. In academic research, more works need to be done to validate sentiment theory and to identify other sentiment proxies that are valuable in real practice. This work can be synthesised with the evidence of overreaction and herding behaviours in Malaysian stock market as discussed in Ali, Ahmad and Anusakumar (2011) and Brahmana, Hooy, and Ahmad (2012b). The theoretical relationship between sentiment, overreaction, and herding is explained in Kukacka and Barunik (2013). Meanwhile, managing sentiment risk is important in investment practice. In policy, ways to mitigate excessive behavioural risks have to be incorporated in the capital market governance policy framework.

To this end, on the basis of theoretical framework discussed in this paper, we argue that so long as it is human and not a machine who organises the market, every investors, stocks, and markets are affected by waves of sentiment on a different degree due to various reasons as discussed in the article. These findings could be corroborated with other stock markets in countries having similar social, institutional, and regulatory environments with Malaysia for validation and generalisation.

NOTES

1. There are various alternatives available for statistical data disaggregation procedures. This research use the interpolation method because of its advantages of having a lower mean absolute error and root mean squared error compared to other methods as summarised in Chan (1993) comparative study.
2. Agribusiness and commodities stocks are more defensive in nature (Zapata, Detre, & Hanabuchi, 2012). Other industry classification is following Miao and Peng (2007), Held (2009), and Nagy and Ruban (2011).
3. Source: Tuyon and Ahmad (2016).
4. In reference to Pesaran et al. (2001), there are five cases as an options for testing the cointegrating Bound tests; Case 1: no intercepts and no trends, Case 2: restricted intercepts and no trends, Case 3: unrestricted intercepts and no trends, Case 4: unrestricted intercepts and restricted trends, and Case 5: unrestricted intercepts and unrestricted trends.

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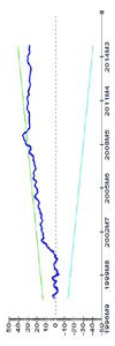
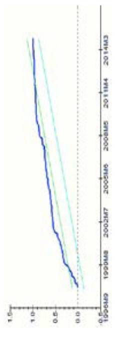
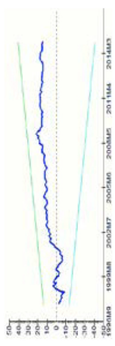
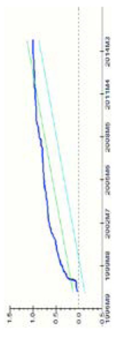
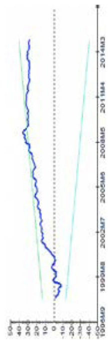
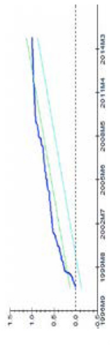
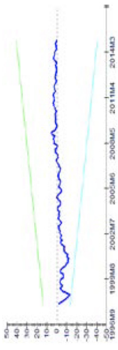
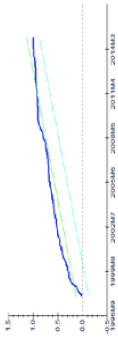
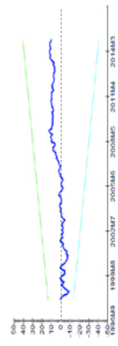
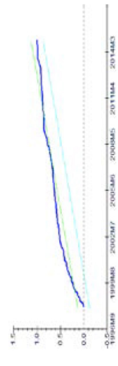
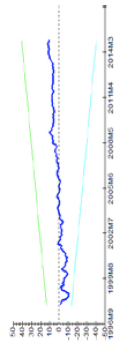
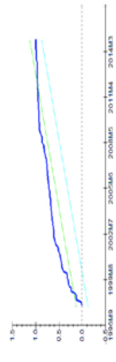
APPENDIX

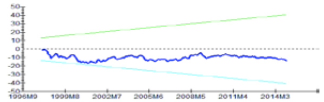
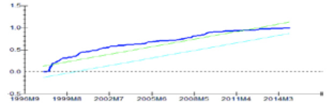
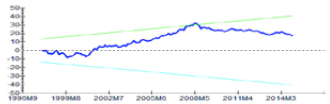
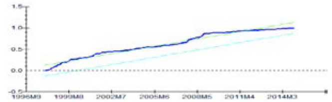
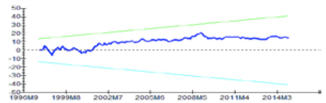
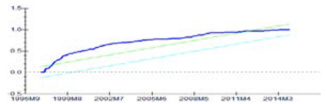
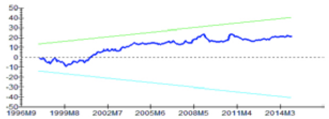
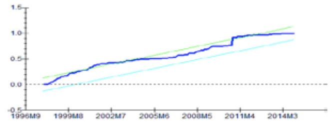
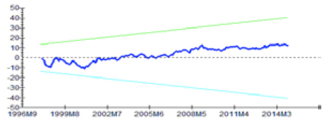
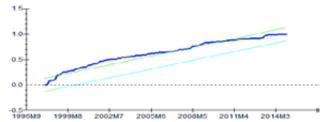
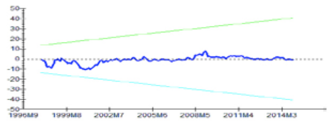
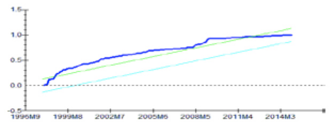
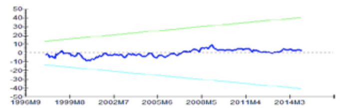
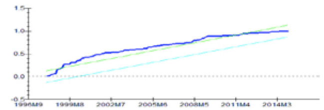
Summary of stability relationships test

Table 8
Summary of stability relationships test

Segmentations/ Models/ Indices		CUSUM	CUSUMSQ
Big/ stable firms	BM KLCI		
	BM 100		
	BM Emas		
Small/ speculative firms	BM 70		
	BM Small Cap		
	BM Fledgling		

(continued on next page)

Table 8: (*continued*)

Segmentations/ Models/ Indices		CUSUM	CUSUMSQ
Defensive industry	Consumer		
	Plantation		
	Trade & Services		
Cyclical industry	Mining		
	Property		
	Finance		
	Construction		

Note: The dotted straight lines represent critical bounds at 5% significance level.

REFERENCES

Akerlof, G. A., & Shiller, R. J. (2009). *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism*. New Jersey: Princeton University Press.

Akhtar, S., Faff, R., Oliver, B., & Subrahmanyam, A. (2011). The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns. *Journal of Banking and Finance, 35*, 1239–1249. http://dx.doi.org/10.1016/j.jbankfin.2010.10.014

Akhtar, S., Faff, R., Oliver, B., & Subrahmanyam, A. (2012). Stock salience and the asymmetric market effect of consumer sentiment news. *Journal of Banking and Finance*, *36*, 3289–3301. http://dx.doi.org/10.1016/j.jbankfin.2012.07.019

Ali, R., Ahmad, Z., & Anusakumar, S. V. (2011). Stock market overreaction and trading volume: Evidence from Malaysia. *Asian Academy of Management Journal of Accounting & Finance*, *7*(2), 103–119.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis, 48*(1), 245–275. http://dx.doi.org/10.1017/S0022109012000592

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*, 1645–1680. http://dx.doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives, 21*(2), 129–151. http://dx.doi.org/10.1257/jep.21.2.129

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, *104*(2), 272–287. http://dx.doi.org/10.1016/j.jfineco.2011.11.002

Bandopadhyaya, A., & Jones, A. L. (2006). Measuring investor sentiment in equity markets. *Journal of Asset Management*, *7*(3), 208–215. http://dx.doi.org/10.1057/palgrave.jam.2240214

Barberis, N. C., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307–343. http://dx.doi.org/10.1016/ S0304-405X(98)00027-0

Baur, M. N., Quintero, S., & Stevens, E. (1996). The 1986-88 stock market: Investor sentiment or fundamentals? *Managerial and Decision Economics*, *17*, 319–329. http://dx.doi.org/10.1002/(SICI)1099-1468(199605)17:3<319::AID-MDE776>3.0.CO;2-0

Becher, D. A., Jensen, G. R., & Mercer, J. M. (2008). Monetary policy indicators as predictors of stock returns. *Journal of Financial Research, 31*(4), 357–379. http://dx.doi.org/10.1111/j.1475-6803.2008.00243.x

Bekaert, G., & Harvey, C. R. (2002). Research in emerging markets finance: Looking to the future. *Emerging Markets Review*, 3, 429–448. http://dx.doi.org/10.1016/S1566-0141(02)00045-6

Black, F. (1986). Noise. *Journal of Finance, 41*(3), 529–543. http://dx.doi.org/10.1111/j.1540-6261.1986.tb04513.x

Bos, T., & Anderson, S. (1988). Consumer sentiments and share price behaviours. *Journal of Behavioural Economics*, *17*(2), 113–118. http://dx.doi.org/10.1016/0090-5720(88)90002-2

Bos, T., Ding, D., & Fetherston, T. A. (1998). Searching for periods of volatility: A study of the behaviours of volatility in Thai stocks. *Pacific-Basin Finance Journal*, *6*, 295–306. http://dx.doi.org/10.1016/S0927-538X(98)00014-6

Brahmana, R. K., Hooy, C. W., & Ahmad, Z. (2012a). Psychological factors on irrational financial decision making. *Humanomics, 28*(4), 236–257. http://dx.doi.org/10.1108/08288661211277317

Brahmana, R. K., Hooy, C. W., & Ahmad, Z. (2012b). The role of heard behaviours in determining the investor's monday irrationality. *Asian Academy of Management Journal of Accounting and Finance, 8*(2), 1–20.

Brooks, C., Rew, A., & Ritson, S. (2001). A trading strategy based on the lead-lag relationship between the spot index and futures contract for the FTSE 100. *International Journal of Forecasting*, *17*, 31–44. http://dx.doi.org/10.1016/S0169-2070(00)00062-5

Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *The Royal Statistical Society, Series B*, *37*(2), 149–192.

Burghardt, M. (2011). *Retail investor sentiment and behaviours: An empirical analysis.* Germany: Gabler Verlag. http://dx.doi.org/10.1007/978-3-8349-6170-9

Casey, G. P., & Owen, A. L. (2013). Good news, bad news, and consumer confidence. *Social Science Quarterly, 94*(1), 292–315. http://dx.doi.org/10.1111/j.1540-6237.2012.00900.x

Chan, W. S. (1993). Disaggregation of annual time-series data to quarterly figures: A comparative study. *Journal of Forecasting, 12*, 677–688. http://dx.doi.org/10.1002/for.3980120816

Chang, C. Faff, R. W., & Hwang, C. Y. (2012). Local and global sentiment effects and the role of legal, information and trading environments. Available at SSRN: http://dx.doi.org/10.2139/ssrn.1800550 .

Chen, S. S. (2011). Lack of consumer confidence and stock returns. *Journal of Empirical Finance*, *18*, 225–236. http://dx.doi.org/10.1016/j.jempfin.2010.12.004

Chen, M. P., Chen, P. F., & Lee, C. C. (2013). Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence. *Emerging Markets Review*, *14*, 35-54. http://dx.doi.org/10.1016/j.ememar.2012.11.001

Chou, P. H., Ho, P. H., & Ko, K. C. (2012). Do industries matter in explaining stock returns and asset-pricing anomalies? *Journal of Banking & Finance*, *36*(2), 355–370. http://dx.doi.org/10.1016/j.jbankfin.2011.07.016

Chung, S., Hung, C., & Yeh, C. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance*, *19*, 217–240. http://dx.doi.org/10.1016/j.jempfin.2012.01.002

Corredor, P., Ferrer, E., & Santamaria, R. (2015). Sentiment-prone investors and volatility dynamics between spot and futures markets. *International Review of Economics and Finance*, *35*, 180–196. http://dx.doi.org/10.1016/j.iref.2014.09.013

Dash, S. R., & Mahakud, J. (2013). Investor sentiment and stock return: Do industries matter? *Journal of Applied Economic Research*, *7*(3), 315–349. http://dx.doi.org/10.1177/0973801013491530

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of political Economy*, 703–738. http://dx.doi.org/10.1086/261703

Dirks, F. C. (1958). Recent investment return on industrial stocks. *Journal of Finance, 13*(3), 370–385. http://dx.doi.org/10.1111/j.1540-6261.1958.tb04202.x

Dow, S. C. (2011). Contagion, market sentiment and financial instability. *Cambridge Journal of Economics*, *35*, 233–249. http://dx.doi.org/10.1093/cje/beq029

Ellis, A. (1976). The biological basis of human irrationality. *Journal of Individual Psychology*, *32*(2), 145–168.

Ellis, A. (1991). The revised ABC's of rational emotive therapy. *Journal of Rational-Emotive and Cognitive-Behaviours Therapy, 9*(3), 139–172. http://dx.doi.org/10.1007/BF01061227

Fast, M., Hertel, F., & Clark, W. W. (2014). Economics as a science of human mind and interaction. *Theoretical Economics Letters*, *4*, 477–487. http://dx.doi.org/10.4236/tel.2014.46060

Fisher, K., & Statman, M. (2003). Consumer confidence and stock returns. *Journal of Portfolio Management, 30*(1), 115–127. http://dx.doi.org/10.3905/jpm.2003.319925

Ghasemi, A., & Zahediasl, S. (2012). Normality test for statistical analysis: A guide for non-statisticians. *International Journal of Endocrinology Metabolism*, *10*(2), 486–489. http://dx.doi.org/10.5812/ijem.3505

Gordon, M. J., & Shapiro, E. (1956). Capital equipment analysis: The required rate of profit. *Management Science*, *3*, 102–110. http://dx.doi.org/10.1287/mnsc.3.1.102

Garcia, M. J. (2013). Financial education and behavioural finance: New insights into the role of information in financial decisions. *Journal of Economic Surveys, 27*(2), 297–315. http://dx.doi.org/10.1111/j.1467-6419.2011.00705.x

Held, J. (2009). Why it is (still) all about sectors – Sectors as a tool for asset allocation. *Journal of Indexes*, *12*(5), 10-56.

Jansen, W., & Nahuis, N. (2003). The the stock marketand consumer confidence: European evidence. *Economics Letters*, *79*, 89–98. http://dx.doi.org/10.1016/S0165-1765(02)00292-6

Jones, B. D. (1999). Bounded rationality. *Annual Review of Political Science, 2*, 297–321. http://dx.doi.org/10.1146/annurev.polisci.2.1.297

Kahneman, D. (2003). Maps of bounded rationality. *American Economic Review, 93*(5), 1449–1475. http://dx.doi.org/10.1257/000282803322655392

Kalay, A., & Wohl, A. (2009). Detecting liquidity traders. *Journal of Financial and Quantitative Analysis*, *44*(1), 29–54. http://dx.doi.org/10.1017/S0022109009090085

Kaplanski, G., & Levy, H. (2010). Sentiment and stock prices: The case of aviation disaster. *Journal of Financial Economics*, *95*, 174–201. http://dx.doi.org/10.1016/j.jfineco.2009.10.002

Kearney, C. (2012). Emerging markets research: Trends, issues and future directions. *Emerging Markets Review*, 13, 159–183. http://dx.doi.org/10.1016/j.ememar.2012.01.003

Keynes, J. M. (1937). The general theory of employment. *Quarterly Journal of Economics*, *51*, 209–223. http://dx.doi.org/10.2307/1882087

Kim, K. A., & Nofsinger, J. R. (2008). Behavioral finance in Asia. *Pacific-Basin Finance Journal*, *16,* 1–7. http://dx.doi.org/10.1016/j.pacfin.2007.04.001

Kling, G., & Gao, L. (2008). Chinese institutional investors' sentiment. *Journal of International Financial Markets, Institutions and Money*, *18*(4), 374–387. http://dx.doi.org/10.1016/j.intfin.2007.04.002

Kukacka, J., & Barunik, J. (2013). Behavioural breaks in the heterogeneous agent model: The impact of herding, overconfidence, and market sentiment. *Physica A: Statistical Mechanics and its Applications*, *392*(23), 5920–5938.

Kumar, A., & Lee, C. (2006). Retail investor sentiment and return co-movements. *Journal of Finance*, *61*(5), 2451–2486. http://dx.doi.org/10.1111/j.1540-6261.2006.01063.x

Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy. *Journal of Banking and Finance, 34*, 134–149. http://dx.doi.org/10.1016/j.jbankfin.2009.07.010

Kyle, A. (1985). Continuous auction and insider trading. *Econometrica*, *53*, 1315–1336. http://dx.doi.org/10.2307/1913210

Lachowska, M. (2011). What do indexes of consumer confidence tell us? *Employment Research Newsletter*, *18*(3), 1–4. http://dx.doi.org/10.17848/1075-8445.18(3)-1

Lawrence, E. R., McCabe, G., & Prakash, A. J. (2007). Answering financial anomalies: Sentiment-based stock pricing. *Journal of Behavioural Finance*, *8*(3), 161–171. http://dx.doi.org/10.1080/15427560701547248

Lee, C., Shleifer, A., & Thaler, R. (1991). Investor sentiment and the close-end fund puzzle. *Journal of Finance*, *46*, 75–109. http://dx.doi.org/10.1111/j.1540-6261.1991.tb03746.x

Leger, L., & Leone, V. (2008). Changes in the risk structure of stock returns: Consumer confidence and the dotcom bubble. *Review of Financial Economics*, *17*, 228–244. http://dx.doi.org/10.1016/j.rfe.2007.08.001

Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies*, *19*(4), 1499–1529. http://dx.doi.org/10.1093/rfs/hhj038

Luo, X., Zhang, J., & Duan, W. (2013). Social media and firm stock value. *Information Systems Research*, *24*(1), 146–163. http://dx.doi.org/10.1287/isre.1120.0462

Majumder, D. (2014). Asset pricing for inefficient markets: Evidence from China and India. *Quarterly Review of Economics and Finance*, *54*, 282–291. http://dx.doi.org/10.1016/j.qref.2013.12.007

Mat Nor, F., Ibrahim, I., & Rashid, M. (2013). Exposure to investor sentiment in Malaysia: Services versus manufacturing stocks. *Global Business and Economics Anthology, 1*, 239–248.

Mat Nor, F., Rashid, M., Ibrahim, I., & Yunyi, B. (2014). Investor sentiment and bank deposits in Malaysia: Do bank managers time the market while pricing deposits? *Journal of Finance and Financial Services*, *1*(1), 71–84.

Menkhoff, L., & Rebitzky, R. R. (2008). Investor sentiment in the US-dollar: Longer-term, non-linear orientation on PPP. *Journal of Empirical finance*, *15*(3), 455–467. http://dx.doi.org/10.1016/j.jempfin.2007.09.001

Miao, H., & Peng, W. (2007). Why A-share market volatility is high. *China Economic Issues, 4*(7), 1–13.

Mohamad, S., Hassan T., & Ariff, M. (2007). Research in an emerging Malaysian capital market: A guide to future direction. *International Journal of Economics and Management*, *1*(2), 173–202.

Morck, R., Shleifer, A., & Vishny, R. W. (1990). The stock market and investment: Is the market a sideshow? *Brookings Papers on Economic Activity*, *2*, 157–215. http://dx.doi.org/10.2307/2534506

Murphy, A. (2012). Biology-induced effects on investor psychology and behaviours. *International Review of Financial Analysis*, *24*, 20–25. http://dx.doi.org/10.1016/j.irfa.2012.07.001

Nagy, Z., & Ruban, O. (2011). Does style make the sector. *MSCI Applied Research*, 1–17.

Pesaran, M. H., & Shin, Y. (1998). An autoregressive distributed-lag modelling approach to cointegration analysis. *Econometric Society Monographs*, *31*, 371–413. http://dx.doi.org/10.1017/ccol0521633230.011

Pesaran, M. H., Shin, Y., & Smith, R. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*, 289–326. http://dx.doi.org/10.1002/jae.616

Premack, D., & Woodruff, G. (1978). Does the chimpanzee have a 'theory of mind'? *Behavioural Brain Science*, *4*, 515–526. http://dx.doi.org/10.1017/S0140525X00076512

Rashid, M., Hassan, M. K., & Yein, N. Y. (2014). Macroeconomics, investor sentiment, and Islamic stock price index in Malaysia. *Journal of Economic Cooperation and Development, 35*(4), 221–236.

Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin Finance Journal*, *11*, 429–437. http://dx.doi.org/10.1016/S0927-538X(03)00048-9

Rushdi, M., Kim. J. H., & Silvapulle, P. (2012). ARDL bound test and robust inference for the long run relationship between real stock returns and inflation in Australia. *Economic Modelling*, *29*, 535–543. http://dx.doi.org/10.1016/j.econmod.2011.12.017

Safa, M. F., & Maroney, N. C. (2012). Bid-ask spread, futures market sentiment and exchange rate returns. *Journal of Economic Cooperation & Development*, *33*(4), 63–85.

Sanford, C. S. (1994). Financial markets in 2020. *Economic Review-Federal Reserve Bank of Kansas City*, *79*(1), 19–28.

Schmeling, M. (2007). Institutional and individual sentiment: Smart money and noise trader risk? *International Journal of Forecasting, 23*, 127–145. http://dx.doi.org/10.1016/j.ijforecast.2006.09.002

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, *16*(3), 394–408. http://dx.doi.org/10.1016/j.jempfin.2009.01.002

Shefrin, H. (2008). *A behavioural approach to asset pricing* (2nd ed.). United States: Elsevier.

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic Perspectives*, *4*(2), 19–33. http://dx.doi.org/10.1257/jep.4.2.19

Simon, H. A. (1955). A behavioural model of rational choice. *Quarterly Journal of Economics*, *69*(1), 99–118. http://dx.doi.org/10.2307/1884852

Slezak, S. L. (2003). On the impossibility of weak-form efficient markets. *Journal of Financial and Quantitative Analysis*, *38*(3), 523–554. http://dx.doi.org/10.2307/4126730

Solt, M. E., & Statman, M. (1988). How useful is the sentiment index? *Financial Analysts Journal*, 45–55. http://dx.doi.org/10.2469/faj.v44.n5.45

Stambaugh, F. R., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*, 288–302. http://dx.doi.org/10.1016/j.jfineco.2011.12.001

Statman, M. (2008). Countries and culture in behavioral finance. *CFA Institute Conference Proceedings Quarterly*, *25*(3), 38-44. http://dx.doi.org/10.2469/cp.v25.n3.6

Statman, M., & Weng, J. A. (2010). Investments accross cultures: Financial attitudes of Chinese-Americans. *Journal of Investment Consulting, 11*(1), 37–44.

Statman, M., Fisher, K. L., & Anginer, D. (2008). Affect in a behavioural asset-pricing model. *Financial Analysts Journal*, *64*(2), 20–29. http://dx.doi.org/10.2469/faj.v64.n2.8

Stets, J. E. (2003). *Emotions and sentiments.* In J. Delamater (Ed.), *Handbook of Social Psychology* (pp. 309-335). New York: Kluwer Academic/Plenum Publishers.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, *62*(3), 1139–1168. http://dx.doi.org/10.1111/j.1540-6261.2007.01232.x

Tuyon, J., & Ahmad, Z. (2014). Psychoanalysis of investors' irrationality and dynamism in stock market. Paper presented at the *16th Malaysian Finance Association Conference (MFA2014)*, Kuala Lumpur, Malaysia.

Tuyon, J., & Ahmad, Z. (2016). Behavioural finance perspectives on Malaysian stock market efficiency. *Borsa Istanbul Review* *16*(1), 43–61. http://dx.doi.org/10.1016/j.bir. 2016.01.001

Yates, J. F., Lee, J., & Bush, J. G. (1997). General knowledge overconfidence: Cross-national variations, response style, and "reality". *Organizational Behavior and Human Decision Processes*, *70,* 87–94. http://dx.doi.org/10.1006/obhd.1997.2696

Yin, F., & Hamori, S. (2011). Estimating the import demand function in the autoregressive distributed lag framework: The case of China. *Economics Bulletin*, *31*(2), 1576–1591.

Zapata, H. O., Detre, J. D., & Hanabuchi, T. (2012). Historical performance of commodity and stock markets. *Journal of Agricultural and Applied Economics, 44*(3), 339–357. http://dx.doi.org/10.1017/S1074070800000468

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does investor sentiment affect stock market crises? Evidence from panel data. *The Financial Review*, *46*, 723–747. http://dx.doi.org/10.1111/j.1540-6288.2011.00318.x