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ASYMMETRIC EFFECTS OF INVESTOR SENTIMENT ON MALAYSIAN SECTORAL STOCKS: A NONLINEAR AUTOREGRESSIVE DISTRIBUTED LAG APPROACH

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ABSTRACT

Extant literature fails to conclusively shed light on the asymmetric effects of market sentiment during bulls and bears, especially for small open markets like Malaysia. This study constructs a sentiment index for Malaysia using Principal Component Analysis. A nonlinear Autoregressive Distributed Lag (ARDL) model is applied to capture and distinguish the optimistic and pessimistic sentiments to justify sectoral stock price movements. Our threefold findings reveal the significant explanatory power of sentiment on sectoral stock prices for both market phases, validated by bound test statistics and error correction terms. Furthermore, the study uncovers long-run asymmetric effects in most sectors (excluding technology) and emphasises their insignificance in the short run, attributable to limited and regulated short selling. Dynamic multiplier graphs underscore the temporal nature of sentiment effects, peaking in the 3rd to 7th months for most stocks, with technology stocks exhibiting an overreaction to negative sentiments. Notably, most stocks respond to positive adjustments, indicating that investors are not driven by loss aversion stemming from diverse market news. These insights are vital for individual traders, fund managers, and regulatory bodies involved in risk assessment and hedging strategy formulation. The study contributes to non-conventional equity analyses, offering valuable perspectives for navigating the complexities of small open markets.

Keywords: Malaysian sectoral stocks, Investor sentiment, Asymmetric effect, Principal component analysis, Nonlinear Autoregressive Distributed Lag (NARDL) modelling

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INTRODUCTION

Doubts about the efficiency of financial markets have led to recent studies on market sentiment to explain the behaviour of securities prices (Shiller, 2002). Since the past decade, empirical studies on asset price movement have been overshadowed by human decision-making attributes, and the literature generally agrees that market sentiment significantly affects stock investments (Haritha & Rishad, 2020; Petit et al., 2019; Li et al., 2017). Among the seminal studies, Baker and Wurgler (2006) verify the effect of investor sentiment in the U.S. stock market, while Petit et al. (2019) and Li et al. (2017) suggest that investor sentiment can be used as a contrarian indicator to predict future stock returns. Baker and Wurgler (2007) further argued that investors are behavioural or physiologically driven and that investment decisions are not always fundamental, which contradicts the efficient market hypothesis.

In an efficient market, when new information is generated, the stock price will change as soon as possible. Some information is not reflected in stock prices because investors are unaware of the news (Peng & Xiong, 2006). The stock market is influenced by information processed by investors. If investor decision-making is skewed because of limited access to complete information, the market will be dominated by psychological elements such as overconfidence, fear, and other emotions. Optimistic information that can positively affect stock prices is known as positive investor sentiment. By contrast, pessimistic information, which has an inverse impact on the stock market, is referred to as negative investor sentiment. However, investors' emotions often overwhelm their rationality, causing stock prices to move away from fundamental values, especially during bear markets. In a bear market, investors are said to be more sensitive and emotional than in a bull market. This is because there is greater "fear of loss" (Kahneman & Tversky, 1979). Later works further suggest that investors are commonly subject to loss aversion. They are more unhappy when they suffer losses than they are happy when they achieve gains[1] (Shiller, 2002; Shefrin, 2002). Consequently, investors' positive and negative sentiments may not have a similar effect on stock price movements (Haritha & Rishad, 2020). For instance, positive and negative information, such as match results released from a soccer game, may magnify investors' reactions to influence stock prices (Dimic et al., 2018).

As a small and open economy, Malaysia has experienced most of the important global booms and shocks in the past three decades. BURSA Malaysia[2] – established as among the top-10 stock exchange in Asia, has been an active but volatile market. In the literature, BURSA Malaysia has exhibited a low degree of market efficiency or weak-form efficiency, where information dissemination is incomplete, and traders are still able to gain abnormal returns using technical analysis (Ling & Abdul-rahim, 2017). In practice, we observe different degrees of price movement in the BURSA during bulls and bears in the past decades (see Figure 1). For instance, the BURSA composite index grew by more than 30% in the early 1990s, after Malaysia was listed as an East Asian Miracle by the World Bank (1993). Stock performance also grew at a moderate pace in 1999–2000, 2002–2007 and 2009–2015 with an average annual return of 20%–30%. However, at some points, the stock performance during bear periods is more drastic. During the Asian Financial Crisis (1997/1998), the Kuala Lumpur Composite Index (KLCI) crashed about 76%, falling from 1,270 to 262.7 points between March 1997 to 1 September 1998. Approximately USD250 billion share value was wiped off. In the following dot-com crisis (2000/2001), BURSA again plunged by 40% from 982 to 584 points between February 2000 and April 2001. Technology stocks fell sharply, by 70.3%. The Global Financial Crisis (2007/2008) witnessed another drastic price collapse of 40.3% from 1,445 to 863 points within 10 months from December 2007 to October 2008. In such events, the movement of stock prices was greatly redirected by investors' fear, and these effects were contagious worldwide. The fundamentals may not work well to justify the price movement and trading volumes in the stock market, especially for small and open markets, such as Malaysia. However, such hypothetical arguments are subject to further investigation.

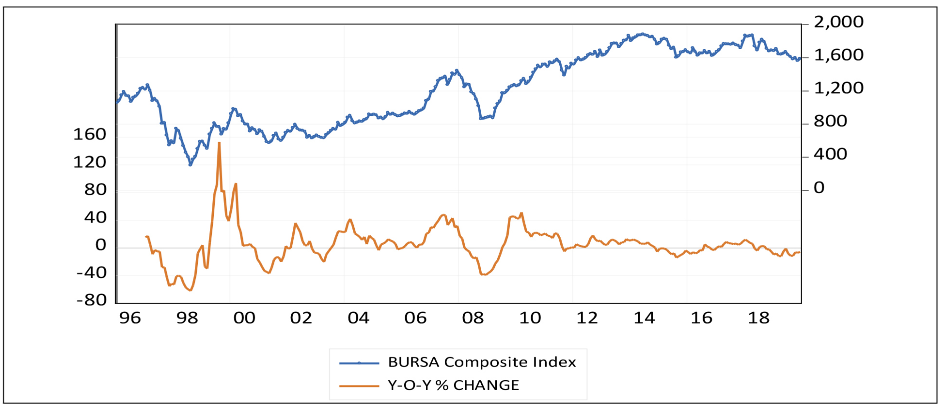

Figure 1: BURSA Malaysia Composite Index and Percentage Changes (%), 1996–2019 (Source: BURSA Malaysia)

The impact of financial turmoil on Malaysian stocks is enormous instantaneously. While booming periods seem to last longer than bearing periods, the BURSA composite index typically plunges at a higher rate compared to stock market recovery. Optimistic sentiment may cause stock overvaluation, whereas pessimistic sentiment leads to stock undervaluation. Both types of sentiment trigger mispricing and deviate stock prices from their fundamental values. Various attempts have been made to justify the asymmetric effect of sentiment on world equity markets, but few have been made for Malaysian sectoral stocks. The supporting literature is scarce to verify the asymmetric effect of investor sentiment, especially for the recent era of fluctuations (see Li et al., 2017; Habibah et al., 2017; Tuyon et al., 2016; Li, 2015; Chen et al., 2013; among others).

In Tuyon et al. (2016), survey-based consumer sentiment index (CSI) and business confidence index that sourced from Malaysian Institute of Economic Research (MIER)[3] were used to reveal the effect of sentiment on the Malaysian market. Chen et al. (2013) and Li et al. (2017), on the other hand, adopted the BW index developed by Baker and Wurgler (2006). Whereas Habibah et al. (2017) used the Google Search Volume Indices (GSVI) and Investor Fear Gauge Volatility Index (VIX) as measurement of market sentiment. These non-standard measurements have resulted in different findings. The MIER surveys, though consistently conducted, the coverage focused more on consumer spending and industrial outputs but has not inclusively measured the changes of sentiments in the financial and capital markets. On the other hand, the BW index is more suitable for addressing corporate sentiment in the U.S. and global markets. However, we need a more precise and accurate investment sentiment index that explains the behaviour of Malaysian sectoral stocks in a time-series manner. In this regard, the GSVI is beyond our consideration. In addition, the VIX is not suitable for justifying the asymmetric effect of sentiment within our methodology framework. For example, an increase in market volatility can represent either optimistic buying pressure or negative investor emotions; thus, it is difficult to explain the difference in volatility changes. Therefore, multiple investor sentiment proxies are justifiable within the context of our study to construct a composite investor sentiment index.

Considering the discussion, we deploy six proxies that best describe investor sentiment in the Malaysian stock market. The selected sentiment proxies are Trading Turnover (TV_t), New IPO fund ($NIPO_t$), Change in Money Supply M2 (define as $CM2_t = M2_t - M2_{t-1}$), Exchange Rate of MYR/USD (ER_t), KLIBOR 1-Month Rate (IR_t) and Consumer Sentiment Index (CSI_t) published by the MIER.

We include trading turnover as a measure of stock market liquidity because it is closely linked to investor sentiment (Baker & Stein, 2004). Pagan and Sossounov (2003) report that higher sentiment prevails in bull markets and lower sentiment prevails in bear markets. Trading turnover can capture such trends in the stock market and is, therefore, an important indicator of investor sentiment. Chen et al. (2014) also incorporated the trading volume to capture market liquidity of Chinese stock market and construct investor sentiment index. In addition to the market liquidity captured by trading turnover, we include the new initial public offerings (IPO) fund to capture the nuanced aspect of market sentiment linked to the behaviour of investors participating in newly issued shares. This decision to include a new IPO fund aligns with the idea that sentiment, as reflected in IPO activities, can significantly drive changes in stock prices. Hence, it adds an additional dimension that contributes to a more comprehensive sentiment index that can better predict changes in Malaysian sectoral stocks. Third, we include money supply to incorporate sentiments stemming from monetary policy. Retail investors in Malaysia often have limited investment channels. Therefore, a higher money supply (loose monetary policy) leads to excess capital in the stock market. Thus, higher money supply is linked to higher investor sentiment. Overall, changes in money supply translate into changes in other economic conditions, such as interest rates, inflation, and investor expectations, all of which ultimately contribute to investor sentiment in the stock market.

Fourth, in the sentiment index construction, we include the exchange rate (MYR/USD) because it is closely linked to the movement of capital flows. For instance, depreciation in Malaysian ringgit discourages foreign investors from demanding Malaysian financial assets, and vice versa. This decline (increase) in demand from international investors leads to lower (higher) investor sentiments. Hence, exchange rate is an important element of investor sentiment and can influence stock prices. Fifth, we include the short-term interest rate (KLIBOR 1-Month Rate) because of its potential to influence borrowing costs, investment decisions, and the attractiveness of different classes of assets. For instance, a spike in the short-term interest rate makes equities more attractive than fixed-income securities (e.g., bonds), contributing to positive investor sentiment and higher asset prices. Thus, interest rates play an important role in shaping investor behaviour and stock market dynamics. Finally, integrating the consumer confidence index is based on the fact that it depicts the overall economic outlook and potential market movement. This is a good indicator of public confidence in the overall economy, which in turn affects consumption and investment decisions. In summary, the consideration of these six proxies is driven by strong economic theory for constructing an investor sentiment index and predicting changes in Malaysian sectoral stocks.

This study constructs a specific investor sentiment index for BURSA using selected economic and financial variables by employing a factor analysis technique and Principal Component Analysis (PCA). This investment sentiment index is then used to analyse the relationship of sectoral stocks-sentiment for consumer products, industrial products, finance, plantation, technology, construction, and property during 1996M1–2019M12. The study period comprises of stock booms and crashes. We try to extract optimistic (positive) and pessimistic (negative) elements from investor sentiment to evaluate the potential asymmetric effects on sectoral prices. Such goal is accomplished through the NARDL modelling procedure advanced by Shin et al. (2014). In NARDL, a cointegration estimation is possible if the model's regressors are purely I (0), purely I (1), or mutually cointegrated. NARDL also allows us to simultaneously examine the asymmetry and nonlinear relationship between investor sentiment and stock prices in both the long and short run. Even though NARDL does not directly model asymmetric error correction, the asymmetric adjustment patterns of the disequilibrium between stock prices and investor sentiment (e.g., pessimistic, optimistic) can still be observed through dynamic multipliers. A Wald-test is also conducted to provide empirical evidence of asymmetry in both the short- and long-run. To this end, our study fills the literature gap by answering two research questions:

1. To what extent did investor sentiment impact sectoral stock prices in BURSA Malaysia?
2. Have sentiment effects been symmetric or asymmetric?

LITERATURE REVIEW

The efficient market hypothesis, also known as EMH, is the fundamental theory of capital market efficiency, in which all investors in the market are competent with the given information in asset pricing prediction (Shostak, 1997). Under the assumption of EMH, the market adjusts asset pricing effectively when new information is disclosed to the market. Thus, the stock market cannot outperform or achieve abnormal profits for all the market participants. Old school academic and financial economists have widely accepted the EMH concept. They believe that stock price movements and future market returns can be predicted based on past information such as interest rates, cross-sectional data, and other economic indicators. However, Peng and Xiong (2006) argue that investors may not be aware of all news due to market imperfections; hence, some information is not reflected in the stock price.

Malkiel (2003) pointed out that a new generation of economists and statisticians believe that the stock market was least partially predictable based on past information in the stock market. The movement of asset prices also involves psychological and other behavioural variables, which may be irrational during market bubbles or crashes. The resulted market inefficiency due to bubbles and financial crisis had enhanced the idea of "contrarian predictor" (Baker & Wurgler, 2007; Baker et al., 2012). The contrarian predictor concept describes the optimistic view that investors cause overvaluation of stock prices, whereas pessimistic sentiment leads to undervaluation. However, it is believed that the mispricing of stock prices will be adjusted and reverted to their fundamental values in the long term. Similarly, Brown and Cliff (2005) reveal that investors are willing to trade and buy at a higher price on a specific stock during a boom, as they believe that the stock price will rise further. By contrast, excessive pessimistic sentiment causes investors to sell stocks below their fundamental value. These "buy high sell low" behaviours are irrational, and these actions dilute the portfolio investment profit. Baker and Wurgler (2006; 2007) also concluded that the investor sentiment effect would be greater than the speculative type of stock. Therefore, investor sentiment results may vary based on the characteristics of stocks and industries. Haritha and Rishad (2020), for instance, discovered an unbalanced association of sentiment-returns when they separated the mood index into positive and negative emotions. Excess market returns are influenced by positive emotion, whilst negative market returns are influenced by negative sentiment. Extant studies also address the role of tone in corporate communications on initial public offerings (Maximiliano et al., 2019), shareholder disputes on liquidity commonality (Wang, 2022), soccer game results on stock returns (Dimic et al., 2018) and the effect of aviation disasters on stock prices (Demir, 2015; Kaplanski & Levy, 2010).

As for the Malaysian case, Tuyon et al. (2016) used MIER's survey-based Consumer Sentiment Index (SC) and the Business Condition Survey (BC). These two proxies are significant to the positive relationship to return in cyclical stocks but rarely significant in small and defensive stocks. Overall, SC provides a better interpretation of stock returns than SB. However, the financial aspect of sentiment was not taken into account. Another study by Chen et al. (2013) included Malaysia as part of a panel series comprising 11 emerging Asian stock markets. They extended the literature by analysing the asymmetric effects of investor sentiment on the cross-industry stock returns of 10 industries. These industries include basic materials, consumer goods, consumer services, financial, healthcare, industrial, oil and gas, technology, telecommunications and utilities. This study finds that the investor sentiment effect contains local and global sentiment. In line with Baker and Wurgler (2006; 2007), their findings reveal that the investor sentiment effect varies by industry characteristic. On the other hand, the presence of event-based sentiment effects such as the Ramadan effect (religious festivals) is evident in 14 Muslim countries, including Malaysia (Białkowski et al., 2012). The cumulative abnormal returns are significant in that investors tend to buy stocks at the beginning of the Ramadan months and sell stocks before the end of Ramadan.

Good feelings about religious activities have positively impacted stock prices, but the effect diminished during the global financial crisis of 2007/2008. This could be due to the loss aversion among investors, who are more concerned about the loss instead of profit (Shiller, 2002; Shefrin, 2002; Kahneman & Tversky, 1979). In other words, investors might be impatient to close their position to sell in the pessimistic market but hesitate to make a buy decision in the optimistic market. Hence, some scholars suggest that pessimistic sentiment has a greater impact than optimistic sentiment (Li et al., 2017; Li, 2015). The recent literature also confirms that the effects of positive and negative sentiment on stocks are asymmetric (Chen et al., 2013; Li et al., 2017; Habibah et al., 2017). However, evidence about the degree and magnitude of the asymmetric effect between optimistic and pessimistic individuals is still far from conclusive.

The above issue remains unsolved, possibly attributable to the non-standard but different measurements of sentiment. Baker and Wurgler (2006) proposed a BW index, which was using the PCA approach with six proxies to capture investor sentiment in the U.S. stock market. In the Asian stock market, Chen et al. (2014) developed a new measure of investor sentiment index by modifying the BW index for China due to the relatively immature behaviour of the Chinese stock market compared to other developed countries, such as the US. They combined both market and economic variables into their refined sentiment index using the PCA approach. Habibah et al. (2017), on the other hand, used the GSVI and VIX as measurement of market sentiment. Their result is contrary to the literature, in which investor sentiment has a significant symmetric effect on stock returns in the S&P500 U.S. market. Anusakumar et al. (2017) then used the trading volume of stock as the main indicator for investor sentiment. From other perspectives, corporate response to the stock market represents investor sentiment in the stock market. To lower corporate capital costs, managers can choose to issue new shares and offer more IPO when investor sentiment is high. Corporate response sentiment is sometimes called manager sentiment and can also be used as an indicator to predict stock returns (Jiang et al., 2019).

To this end, the literature has arrived at several conclusions regarding the impact of market sentiment on stocks. However, the measurement of sentiment and asymmetric effects is not in consensus, which offers room for further investigation, especially for sectoral stocks of small and emerging markets such as Malaysia.

RESEARCH METHOD AND DATA

Data Description

This article analyses monthly data from January 1996 to December 2019, with a total of 288 observations. Our study period covers the bulls and bears of equities that entailed with large uncertainties and price fluctuation. The study period offers good opportunity to assess the impacts of market sentiment on stock investment. Despite the booming era in 1996, 1999/2000, 2006/2007 and 2010 to 2015, the analysis also includes phases of shocks, e.g., Asia Financial Crisis (March 1997–August 1998), Dot-com Bubble Burst (April 2000–April 2001), and Global Financial Crisis (January 2008–December 2008).

A two-step research procedure is performed. First, the investor sentiment index is constructed based on six selected equity and financial market variables. Second, the stock-sentiment dynamic relationship is examined. The asymmetric effect of sentiment on BURSA sectoral stock prices is further investigated using the NARDL procedure. In addition to the large-cap BURSA Malaysia, we have segmented the stock indexes by seven major sectors with highest trading volumes, namely the Consumer Products, Industrial Product, Finance, Plantation, Technology, Construction and Property. Other sectoral stocks are excluded from this study due to the low trading volumes and data inconsistency. The dependent variables are defined as $y_t = \ln (\textit{Sectoral Stock Index}_t)$ and all data are sourced from CEIC database, BURSA, Central Bank of Malaysia and MIER.

Measuring Investor Sentiment

Following the spirit of Chen et al. (2014), this paper constructs the investor sentiment index (ISI) using the PCA and factor analysis. A total of six sentiments proxies that best describe Malaysian investor sentiment are being considered. The selected sentiment proxies are TV_t, $NIPO_t$, $CM2_t = M2_t - M2_t - 1$, ER_t, IR_t and CSI_t. The existing CSI that is published by MIER is quarterly based, and we have converted CSI into monthly series by using the interpolation method (cubic spline). Some proxies that suggested by literature are excluded from this article due to data unavailability and less relevant to the domestic market context. Details of the sentiment construction are presented in Table 1.

Empirical Model

The non-linear ARDL (NARDL) approach has been used in this study to assess the uneven effect of positive and negative sentiments on BURSA sectoral stocks. NARDL is the model developed by Shin et al. (2014) to use positive and negative decomposition to detect the asymmetric effect in the short-run and long-run estimation. The general form of the NARDL model is defined as:

$$y_{it} = \alpha_0 + \alpha_1 SENT_t^+ + \alpha_2 SENT_t^- + \alpha_3 OIL_t + \alpha_4 IPI_t + \varepsilon_t \tag{1}$$

where the dependent variable comprises of the sectoral stock market indexes (y_{it}) the independent variables are the proxies of positive investor sentiment ($SENT^+{}_t$) and negative investor sentiment ($SENT^-{}_t$) at time t. The control variables then consist of Brent Oil price (OIL_t) and Industrial Production Index (IPI_t). Next, in the following Equations (2) and (3), both independent variables are calculated respectively by using their partial sum of positive and negative changes on investor sentiment, which are presented as below:

$$SENT_T^+ = \sum_{j=1}^{t} \Delta SENT_t^+ = \sum_{j=1}^{t} \max(\Delta SENT_j, 0) \tag{2}$$

$$SENT_T^- = \sum_{j=1}^{t} \Delta SENT_t^- = \sum_{j=1}^{t} \min(\Delta SENT_j, 0) \tag{3}$$

Equation (1) is used to assess the dynamic relationship between the investor sentiment and the stock market index for each sector, in which the sentiment has been split into positive sentiment and negative sentiment in Equations (2) and (3), respectively. The long-term relationship of the positive investor sentiment is captured by α_1, while α_2 while capturing the long-term relationship for negative investor sentiment. To estimate the short-term relation of positive and negative investor sentiment impacts the sector stock index, Equation (1) can be re-fined as:

$$\Delta y_t = \alpha_0 + \beta_0 y_{t-1} + \beta_1 SENT_{t-1}^+ + \beta_2 SENT_{t-1}^- + \beta_3 OIL_{t-1} + \beta_4 IPI_{t-1} + \sum_{i=1}^{p} \beta_5 \Delta y_{t-i} + \sum_{i=0}^{q} (\beta_6^+ SENT_{t-i}^+ + \beta_7^- SENT_{t-i}^-) + \sum_{i=0}^{p} \beta_8 \Delta OIL_{t-i} + \sum_{i=0}^{p} \beta_9 \Delta IPI_{t-i} + \varepsilon_t \tag{4}$$

Where most of the variables already defined in previous equations. The p and q represent the lag orders. The long-term relation of positive sentiment is given by $\alpha_1 = -(\beta_1/\beta_2)$, and the long-term relation of negative sentiment is given by $\alpha_2 = -(\beta_2/\beta_0)$. Besides, $\sum_{t=0}^{q} \beta_6^+$ is the short-term relation of positive sentiment whereas $\sum_{t=0}^{q} \beta_7^-$ captures the short-term relation of negative sentiment to stock index.

NARDL model does not apply for variables, which are I (2) or more, but regressors in the model can be a mixture of I (0) or I (1). Therefore, one must examine the data properties and identify the integration level of each variable by using unit root test. After the integration level of each variable are confirmed in either I (0) and I (1), then the stock–sentiment model in Equation (2) can be estimated. The general to the specific procedure is used to estimate the specification of the NARDL model, including the optimal lags. Then, use the bound testing approach to test for the presence of co-integration in NARDL model (Pesaran et al., 2001). In this technique, the F-statistics is used, and the corresponding error correction model (ECM) shall be estimated to gauge the short-run adjustment towards the long-run equilibrium. Then, the diagnostic tests are conducted to validify the adequacy of the model. These include the LM serial correlation, the Ramsey RESET test, the normality test, the heteroskedasticity test, and stability tests such as CUSUM and CUSUMQ[2] tests. At the fourth step, asymmetric effect of SEN_t^+ and SEN_t^- in the long-run and short-run estimation are tested by conducting through Wald-test. Hence, the relationship between positive and negative investor sentiment can be empirically identified. Once the asymmetric effects are confirmed, the asymmetric cumulative dynamic multiplier for 1% changes of investor sentiment to stock return can be plotted as follows:

$$m_{jn}^{+}(SENT) = \sum_{j}^{n} \frac{\Delta y_{t+j}}{\Delta SENT_{jt-1}^{+}}, n = 0,1,2,3 \ldots \quad (5)$$

$$m_{jn}^{-}(SENT) = \sum_{j}^{n} \frac{\Delta y_{t+j}}{\Delta SENT_{jt-1}^{-}}, n = 0,1,2,3 \ldots \quad (6)$$

where *m(SENT)* is asymmetric cumulative dynamic multiplier for 1% changes of investors sentiment to stock index. While $n = \infty$, the long-term asymmetric relationship of investor sentiment to stock index is equal to multiplier, where $m^{+}_{jn} = \alpha_1$ and $m^{-}_{jn} = \alpha_2$.

EMPIRICAL FINDINGS AND DISCUSSION

This section starts with the construction of composite investor sentiment. The sentiment is constructed using the factor analysis and the PCA method. The first step is to standardise the six sentiment proxy variables, calculate the eigenvalue and eigenvector of their covariance matrix. We can then develop the investor sentiment index as a combination of six variables by using the eigenvector associated with the largest eigenvalue as the corresponding weight. The PCA results are listed in Table 1.

Table 1
Principal component analysis

Factor coefficients:			Rotated loadings: L * inv(T)'		
(Weight of the variables in factor)			Kaiser row weighting		
	F1	F2		F1	F2
TV	0.005794	0.259107	TV	0.073976	0.340049
NIPO	0.041611	0.132413	NIPO	0.147720	0.189840
CM2	–0.014530	0.245591	CM2	0.003330	0.334222
IR	0.087916	–0.273920	IR	0.233005	–0.318417
ER	–0.515503	–0.094027	ER	–0.749890	–0.091583
CSI	0.350767	–0.023768	CSI	0.663749	0.017741
	SUM SQ (Explained variance)			1.0845	0.3735
		Total variance		1.4580	
		Weight of factors		w1	w2
				0.7438	0.2562
Y1 = 0.005794 V + 0.041611 NIPO – 0.515503 ER + 0.032417 IR – 0.01453 CM2 + 0.350767 CSI					
Y2 = 0.259107 V + 0.132413 NIPO – 0.094027 ER – 0.27392 IR + 0.245591 CM2 – 0.023768 CSI					

Notes: Selected sentiment proxies to construct the composite sentiment index are Trading Turnover (TV_t), New IPO fund ($NIPO_t$), Change in Money Supply M2 (define as $CM2_t = M2_t - M2_{t-1}$). Exchange Rate of MYR/USD (ER_t), KLIBOR 1-Month Rate (IR_t) and Consumer Sentiment Index (CSI_t).

Eventually, the Malaysian composite ISI at time t, $SENT_t$ can be constructed based on the specification:

$$SENT_t = \ln (0.0683\ V_t + 0.0742\ NIPO_t + 0.0354\ CIP_t + 0.0702\ CM2_t \\ - 0.0454\ IR_t -(7)\ 0.3195\ ER_t + 0.2291\ CSI_t \quad (7)$$

From Equation (7), we note that the specification output is similar to that of Chen et al. (2014), where all sentiment proxies are positively related to the constructed investor sentiment index (ISI), except for the interest and exchange rates. The constructed sentiment index (SENT) and its decomposed elements of negative (SENT_NEG) and positive (SENT_PSO) sentiments are presented in Table 2 and Figure 2, respectively. Table 2 displays the descriptive analysis of each variable used for NARDL modelling in the next section. These variables include the BURSA composite index (KLSE), seven sectoral stock indexes, sentiment index, and control variables of the Brent oil price and industrial production index (IPI). In addition, the time plots for all variables, including the estimated positive and negative sentiments during bulls and bears (in natural logarithm), are shown in Figure 2.

Table 2
Descriptive statistics

Variables	N	Mean	Median	Max	Min	SD	Skewness	Kurtosis
Sentiment Index								
SENT	287	7.59	7.80	8.65	5.09	0.73	–1.22	4.21
SENT_POS	286	30.14	31.14	54.46	0.39	16.11	–0.29	1.89
SENT_NEG	286	–30.12	–30.48	0.00	–53.66	15.71	0.32	1.97
TV	288	28521.80	30813.50	67102.00	3721.00	14997.95	0.09	2.12
NIPO	288	452.05	89.26	12547.91	0.00	1350.66	6.31	48.88
ER	288	3.59	3.78	4.55	2.48	0.46	–0.57	2.99
IR	288	3.72	3.08	10.98	2.05	1.80	2.45	8.33
CM2	287	6079.79	4546.00	31309.89	–13923.50	8519.12	0.68	3.76
CSI	287	102.57	107.43	133.40	63.80	16.97	–0.44	2.15
Sectoral Stocks								
BURSA	288	7.03	7.09	7.54	5.71	0.40	–0.51	2.34
Consumer	288	5.75	5.71	6.60	4.43	0.56	–0.10	1.71
Industrial	288	4.64	4.66	5.21	3.69	0.34	–0.11	1.89
Finance	288	9.14	9.18	9.82	7.44	0.51	–0.63	2.82
Plantation	288	8.32	8.58	9.13	7.04	0.66	–0.30	1.45
Technology	236	3.31	3.29	4.99	2.41	0.51	0.47	2.91
Construction	288	5.42	5.45	6.38	4.15	0.35	0.06	3.59
Property	288	6.84	6.84	7.99	6.03	0.39	0.66	3.36
Brent oil	288	56.80	54.30	133.87	9.80	32.59	0.47	2.11
IPI	288	79.04	81.19	118.01	40.24	20.67	0.00	2.06

Notes: The Investor Sentiment Index (SENT) was constructed using Trading Volume (TV), new IPO funds (NIPO), Exchange Rate (ER), Interest Rate (IR), Change in M2 (CM2), and Consumer Sentiment Index (CSI). The sectoral stock indexes are the BURSA composite index, consumer products, industrial products, financial services, plantations, technology, construction and property products. Control variables include the Brent oil prices quoted in US dollars per barrel and the IPI as the industrial production index, with base year 2015 = 100. (Sources: KLSE, MIER and Bank Negara Malaysia).

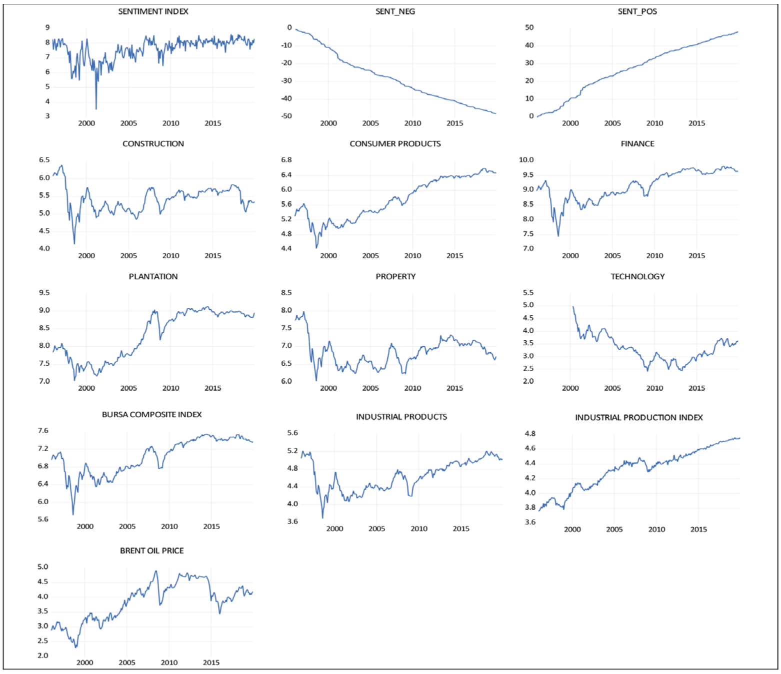

Figure 2: Sentiment indexes, sectoral stock prices and control variables, 1996M1–2019M12 (Source: KLSE, MIER and Bank Negara Malaysia)

Prior to employing the NARDL model, evaluating the order of integration in variables is essential, usually achieved through unit root tests. While the Augmented Dickey-Fuller (ADF) test is frequently used, it possesses limitations like sensitivity to trends and sample size. The modified Dickey Fuller test with Generalised Least Squares (DF-GLS), introduced by Elliott et al. (1996), surpasses ADF in terms of improved power and robustness, particularly in the presence of unknown trends. The DF-GLS test is advocated for its superior performance in small sample sizes and its ability to handle the constraints of the ADF test effectively (Elliott et al., 1996, p. 813). This makes DF-GLS a preferred choice over ADF, offering enhanced robustness and efficiency in unit root testing for autoregressive time series models. The ADF and DF-GLS test results were utilised to determine the integration level of all data series. Incorporating an intercept and selecting optimal lags using the AIC, Table 3 outlines the unit root test analysis. Due to the superior robustness of DF-GLS compared to ADF, our decision relies on the DF-GLS outcomes. Conclusively, based on the DF-GLS results, all variables exhibit first-difference stationarity, meeting the cointegration prerequisite, allowing us to proceed with the NARDL estimation.

Table 3
Unit root tests

Variables	ADF				DF-GLS				Decision
	Level	Lag	1st diff.	Lag	Level	Lag	1st diff.	Lag	I (d)
Dependent variables									
KLCI	–1.3843	11	–5.0327***	10	–1.4094	1	–3.9631***	6	I (1)
Consumer prod.	–0.4994	7	–5.7055***	6	0.3540	0	–8.8389***	1	I (1)
Industrial prod.	–2.4032	10	–4.6166***	10	–1.0933	0	–9.6003***	1	I (1)
Finance	–1.3612	12	–5.2901***	11	–1.6636	10	–3.5811	6	I (1)
Plantation	–0.8122	1	–14.7633***	0	–0.0895	0	–13.8396***	0	I (1)
Technology	–2.7984*	3	–13.8905***	0	–0.1698	0	–2.7236***	2	I (1)
Construction	–4.7105***	10	–6.0586***	13	–1.5894	10	–4.2461***	9	I (1)
Property	–3.8830***	10	–5.3938***	11	–0.7153	1	–14.0482***	0	I (1)
Independent variables									
SENT	–2.3215	5	–6.1552***	15	–1.4859	5	–2.9206**	7	I(1)
SENT_POS	–2.5340	1	–20.3468***	0	–0.4028	1	–2.8823***	5	I(1)
SENT_NEG	–2.0122	2	–20.0786***	0	–0.5113	1	–2.4537**	7	I(1)
OIL	–1.7563	1	–13.7449***	0	–0.5705	1	–13.7658***	0	I(1)
IPI	–0.2159	12	–4.9364***	11	–1.8712	12	–2.9867**	10	I(1)

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Next, to confirm the cointegration relationship, we rely on a bound test (F-statistics) for the NARDL specification that built on the basis of ARDL cointegration (Pesaran et al., 2001). At this point, we use the general-to-specific approach to estimate the stock-sentiment models, and we also carry out diagnostic checks to ensure that the estimates are correctly specified without the serial correlation problem. The optimum lag selection is based on the AIC criterion, where the maximum lags are preset at lag 6. Table 4 presents the Bound Test results. Strong cointegrations among sectoral prices, sentiment index (SENT), and control variables (OIL, IPI) are detected for five sectors, weaker cointegration (10% significance) for plantation and but indecisive for construction. For construction sector, the F-statistic falls within the upper and lower bounds of the critical values. However, the highly significant error correction terms (ECT) of the corresponding short-run models in Table 5 indicate that all the short-run deviations are adjusted towards the long-run equilibriums. Hence, it is fair to conclude that the cointegration path is built on a stable association between stock prices and investor sentiment, which supported by Li et al. (2017) and Habibah et al. (2017).

Table 4
Bound test and cointegration

Model	Optimal lags	Bound test (F-stat)	Conclusion
BURSA	(5, 4, 6, 1, 3)	5.0913***	Cointegrated
Consumer prod.	(4, 4, 6, 1, 0)	4.6819**	Cointegrated
Industrial prod.	(5, 4, 6, 3, 0)	4.4771**	Cointegrated
Finance	(6, 4, 5, 1, 3)	4.9318**	Cointegrated
Plantation	(4, 4, 6, 1, 5)	3.8422*	Cointegrated
Technology	(5, 0, 5, 4, 0)	4.4110**	Cointegrated
Construction	(6, 4, 5, 1, 0)	3.1277	Inconclusive
Property	(1, 4, 6, 1, 0)	4.3954**	Cointegrated
Critical values	1%	5%	10%
Lower bound	3.74	2.86	2.45
Upper bound	5.06	4.01	3.52

Notes: *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively. Optimal lags are selected based on the AIC criterion, where a maximum lag of six is set.

After verifying the long-run cointegration relationship for KLCI, consumer products, industrial products, financial services, and plantation sectors, the next concern is the long- and short-run dynamics of the variables. The estimated NARDL regressions are shown in Tables 5 and 6. We find that positive and negative investor sentiment have a significant impact on all sectoral stock index movements (except for the technology sector) in the long-run estimation. The reported long-run coefficients in response to positive sentiment range from 0.42–0.65, whereas the coefficients' response to negative sentiment range from 0.39–0.57.

As for the technology sector, investor sentiment is only positively significant in the short-run, but negatively related (insignificant) in the long-run. In addition, the results show that domestic industrial production (IPI) performance plays a greater role than oil prices in the Malaysian stock market in the long-run. In the short-run, both IPI and oil price changes are almost equally impactful. Moreover, the impact of short-run sentiment on sectoral stocks is less than the long-run impact. The short-run coefficients in response to positive sentiment range from 0.074 to 0.1398, whereas the coefficients' responses to negative sentiment range from 0.0266 to 0.0605. All ECT show significant and negative signs, suggesting that KLCI and the seven sectoral stocks exhibit short-run adjustments towards the long-run equilibrium once the models are shocked. KLCI demonstrates the fastest adjustment with the ECT coefficient reported at –0.133, whereas technology and property stocks reported the slowest speed of adjustment with ECT = –0.0645 and ECT = –0.0769, respectively. Subsequently, we performed diagnostic checks for the JB normality, serial correlation LM, heteroscedasticity, and CUSUM stability tests for all NARDL models. The diagnostic results are shown in Table 6. Figure 3 shows the plot of the CUSUM stability test.

Table 5
Long-run estimates

Dependent variable	Independent variables				
	Constant	SENT_POS	SENT_NEG	OIL	IPI
BURSA	10.8442 (5.8747)***	0.4249 (6.3414)***	0.3910 (5.8681)***	0.0695 (1.1213)	–1.1168 (–2.3253)**
Consumer	11.4430 (5.8111)***	0.4921 (6.6537)***	0.4330 (5.9062)***	–0.0308 (–0.4437)	–1.6019 (–3.1367)***
Industrial	11.1162 (3.1719)***	0.4901 (4.1816)***	0.4449 (3.7689)***	–0.2148 (–1.9670)**	–1.5314 (–1.6812)*
Finance	14.8978 (5.0023)***	0.4585 (4.6102)***	0.4071 (4.1079)***	0.0701 (0.7397)	–1.6762 (–2.1553)**
Plantation	13.9032 (5.3513)***	0.6125 (6.0654)***	0.5636 (5.6692)***	0.2345 (2.4693)**	–1.7009 (–2.5463)**
Technology	5.6562 (1.0601)	0.2414 (0.9294)	0.2446 (0.9552)	–1.1069 (–5.2259)***	0.5425 (0.4256)

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Table 5 (*Continued*)

Dependent variable	Independent variables				
	Constant	SENT_POS	SENT_NEG	OIL	IPI
Construction	15.1124 (3.5081)***	0.5536 (3.6971)***	0.5105 (3.4280)***	–0.0568 (–0.3970)	–2.4208 (–2.1590)**
Property	23.1049 (3.9189)***	0.6494 (3.4910)***	0.5768 (3.0361)***	–0.1131 (–0.6612)	–4.0472 (–2.5984)***

Notes: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. *t*-statistics are shown in parentheses. OIL = Brent oil price; IPI = Industrial Production Index.

Next, we examine the potential asymmetric effect of positive and negative investor sentiment on stock index movements using F-statistics (Wald-test). Table 7 presents the results. In addition, Figure 4 presents an asymmetric dynamic multiplier plot for all the sectoral stocks. We note that the asymmetric effects of investor sentiment are significant only in the long run for KLCI and six sectoral stocks. However, again, no asymmetry effect was found for technology stock in both the short- and long-run. As for the dynamic multiplier plot in Figure 4, we observe that the asymmetric effects on sectoral stocks are more skewed toward positive sentiments (except for technology stock), implying that investors tend to react more to the optimistic environment. They are not subject to loss aversion, driven by diverse types of market news. However, the dynamic multipliers further indicate that sentiment effects amplify after three months and stabilise after seven months for consumer products, industrial products, finance, plantation, construction, and property stocks.

To this end, the findings show that the constructed investor sentiment index (SENT) justifies and describes the change in Malaysian stock indices, which partly support studies by Li et al. (2017), Habibah et al. (2017) and Tuyon et al. (2016). Investors' bullish moods are rising to drive stock prices up. Nevertheless, this will lead to lower stock returns in the next period because the overvalued stock increases during the exhibition of strong investor sentiment on the market. These findings support H1, as outlined in the preceding section and current literature, such as Haritha and Rishad (2020), Huang et al. (2015), and Baker and Wurgler (2006). However, the index of the technology sector reacts differently to the constructed sentiment index (SENT), where investor sentiment has a negative relationship with the technology stock index. However, this relationship was not significant, and a normality issue was found in the model. This finding provides a signal in supports for H2, in which the impact of investor sentiment varies by industry (Chen et al., 2013).

Table 6
Short-run coefficients and diagnostic statistics

Stock Index (Y)	KLCI	Consumer	Industrial	Finance	Plantation	Technology	Construction	Property
Optimum lag	(5, 4, 6, 1, 3)	(4, 4, 6, 1, 0)	(5, 4, 6, 3, 0)	(6, 4, 5, 1, 3)	(4, 4, 6, 1, 5)	(5, 0, 5, 4, 0)	(6, 4, 5, 1, 0)	(1, 4, 6, 1, 0)
Constant	1.4424 (4.3696)***	1.1470 (4.2628)***	0.8669 (3.3697)***	1.6936 (4.1866)***	1.3077 (3.3957)***	0.4352 (1.1917)	1.3752 (3.2639)***	1.4903 (3.8645)***
ΔY (–1)	0.0644 (1.1099)	0.0126 (0.2210)	–0.0475 (–0.8059)	0.0829 (1.4230)	0.0386 (0.6581)	0.0339 (0.5212)	–0.0301 (–0.5159)	–0.0645 (–3.0273)***
ΔY (–2)	0.1115 (1.9434)*	0.0775 (1.3780)	0.0548 (0.9412)	0.1282 (2.1669)**	0.0695 (1.2031)	0.1224 (1.9283)*	0.1211 (2.0711)**	-
ΔY (–3)	–0.1584 (–2.7109)***	–0.1833 (–3.2512)***	–0.1067 (–1.8425)*	–0.1324 (–2.1914)**	–0.1386 (–2.3171)**	0.1395 (2.1916)**	–0.0826 (–1.4119)	-
ΔY (–4)	–0.1786 (–3.1825)***	-	–0.1032 (–1.9124)*	–0.1653 (–2.9215)***	-	–0.1608 (–2.5666)**	–0.1124 (–2.0877)**	-
ΔY (–5)	-	-	-	0.1008 (1.8360)*	-	-	0.0976 (1.8185)*	-
ΔSENT_POS	0.0848 (5.1296)	0.0740 (5.3884)***	0.0947 (5.6856)***	0.1066 (4.9192)***	0.0833 (4.7983)***	0.0185 (0.9889)	0.1398 (5.3769)***	0.1359 (6.4326)***
ΔSENT_POS (–1)	0.0332 (1.4342)	0.0570 (2.9203)***	0.0279 (1.1656)	0.0169 (0.5697)	0.0345 (1.3650)	-	0.0521 (1.4325)	0.02042 (0.6779)
ΔSENT_POS (–2)	–0.0732 (–3.2107)***	–0.0708 (–3.6306)***	–0.0572 (–2.4139)**	–0.0697 (–2.3299)**	–0.0807 (–3.2585)***	-	–0.0740 (–2.0161)**	–0.0445 (–1.5137)
ΔSENT_POS (–3)	0.0556 (3.1935)***	0.0389 (2.5842)**	0.0561 (3.1248)***	0.0684 (3.1379)***	0.0494 (2.6298)***	-	0.0900 (3.4003)***	0.0607 (2.8829)***
ΔSENT_NEG	0.0330 (2.4696)**	0.0266 (2.4439)**	0.0396 (2.9403)***	0.0511 (2.9195)***	0.0343 (2.3754)**	0.0458 (2.4027)**	0.0605 (2.8800)***	0.0441 (2.5772)**
ΔSENT_NEG (–1)	0.0165 (0.6611)	–0.0149 (–0.7169)	0.0298 (1.1495)	0.0286 (0.8597)	0.0136 (0.5064)	0.1065 (4.3138)***	0.0056 (0.1420)	0.0385 (1.1847)

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Table 6 (*Continued*)

Stock Index (Y)	KLCI	Consumer	Industrial	Finance	Plantation	Technology	Construction	Property
ΔSENT_NEG (–2)	0.0350 (1.4504)	0.0612 (3.0397)***	0.0472 (1.8910)*	0.0272 (0.8629)	0.0771 (2.9253)***	0.0008 (0.0331)	0.0633 (1.6695)*	0.0527 (1.6579)*
ΔSENT_NEG (–3)	–0.1144 (–5.2076)	–0.1043 (–5.6768)***	–0.1034 (–4.5389)***	–0.1117 (–3.9304)***	–0.1315 (–5.5158)***	–0.0758 (–3.1664)***	–0.1134 (–3.3123)***	–0.1103 (–3.8478)***
ΔSENT_NEG (–4)	0.0509 (2.8038)***	0.0296 (1.9236)*	0.0377 (2.0445)**	0.0819 (3.7523)***	0.0262 (1.3284)	0.0313 (1.6046)	0.0955 (3.6765)***	0.0607 (2.6729)***
ΔSENT_NEG (–5)	0.0200 (1.5401)	0.0229 (2.1099)**	0.0314 (2.3965)**		0.0375 (2.6734)***	-	-	0.0260 (1.5744)
ΔBRENT	0.0718 (1.9890)**	0.0508 (1.6755)*	0.1155 (3.0617)***	0.0867 (1.8413)*	0.1023 (2.5944)**	0.0821 (1.4395)	0.1293 (2.3101)**	0.1306 (2.8125)***
ΔBRENT (–1)	-	-	–0.0648 (–1.1405)	-	-	–0.0726 (–0.8094)	-	-
ΔBRENT (–2)	-	-	0.0735 (1.9837)**	-	-	–0.1697 (–1.8646)*	-	-
ΔBRENT (–3)	-	-	-	-	-	0.1588 (2.6805)***	-	-
ΔIPI	0.0456 (0.3032)	–0.1605 (–3.1865)***	–0.1194 (–2.0335)**	–0.0875 (–0.4323)	-0.1013 (-0.5952)	0.0417 (0.4018)	–0.2203 (–2.4001)**	–0.2610 (–3.3717)***
ΔIPI (–1)	-0.0088 (-0.0543)	-	-	–0.1500 (–0.7024)	0.2112 (1.1230)	-	-	-
ΔIPI (–2)	0.3876 (2.5915)**	-	-	0.5224 (2.6083)***	0.4650 (2.4731)**	-	-	-
ΔIPI (–3)	-	-	-	-	–0.3956 (–2.1962)**	-	-	-
ΔIPI (–4)	-	-	-	-	–0.2579 (–1.6006)	-	-	-

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Table 6 (*Continued*)

Stock Index (Y)	KLCI	Consumer	Industrial	Finance	Plantation	Technology	Construction	Property
ECT (–1)	–0.1330 (–4.3048)***	–0.1002 (–4.3407)***	–0.0779 (–3.2873)***	–0.1136 (–3.9644)***	–0.0940 (–4.3481)***	–0.0769 (–3.6903)***	–0.0910 (–3.4267)***	–0.0645 (–3.0273)***
Diagnostic tests								
Adj. R^2	0.9840	0.9942	0.9760	0.9826	0.9930	0.9772	0.9415	0.9654
Functional RESET	0.0458	0.7199	1.3463	0.0103	0.0714	0.1704	1.9897	1.7065
Serial (LM)	1.2975	0.0474	1.1006	1.6339	0.6765	0.2347	1.0392	0.2092
Jarque-Bera	168.8014***	437.1204***	139.1215***	724.9138***	127.1190***	2.9179	475.2329***	166.1394***
Hetero (ARCH)	16.1554***	0.7272	20.9372***	4.5729**	4.1048**	0.1476	1.1017	3.4251*

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

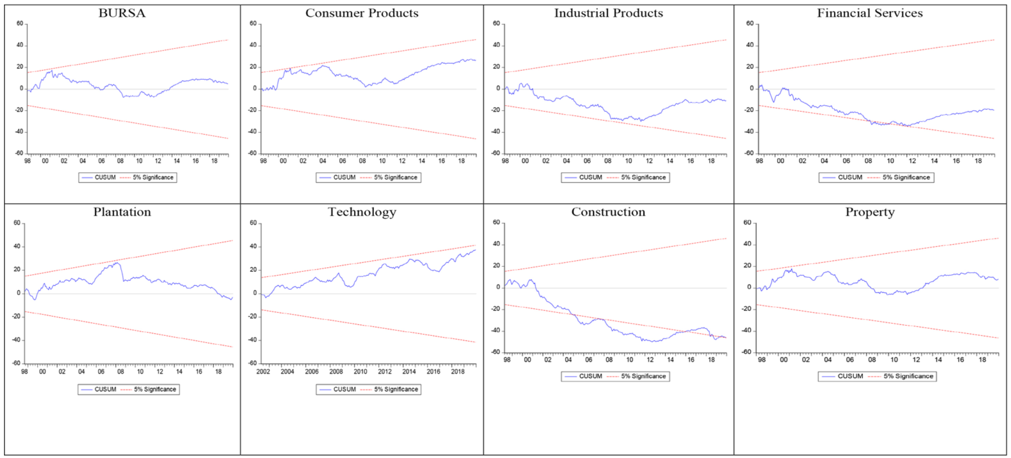

Figure 3: Cumulative Sum (CUMSUM) Graphs

Table 7
Long-run and short-run asymmetric effects of sentiment

Models	Long-run asymmetric	Short-run asymmetric	Conclusion
	F-stats (Wald)	F-stats (Wald)	
KLCI	14.1639***	1.46103	Long-run asymmetry
Consumer prod.	20.7622***	1.854347	Long-run asymmetry
Industrial prod.	9.9447***	0.098513	Long-run asymmetry
Finance	14.1868***	1.3242	Long-run asymmetry
Plantation	8.5037***	0.0071	Long-run asymmetry
Technology	0.0272	0.3917	No asymmetry
Construction	5.3575**	1.5209	Long-run asymmetry
Property	11.0155***	0.0994	Long-run asymmetry

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

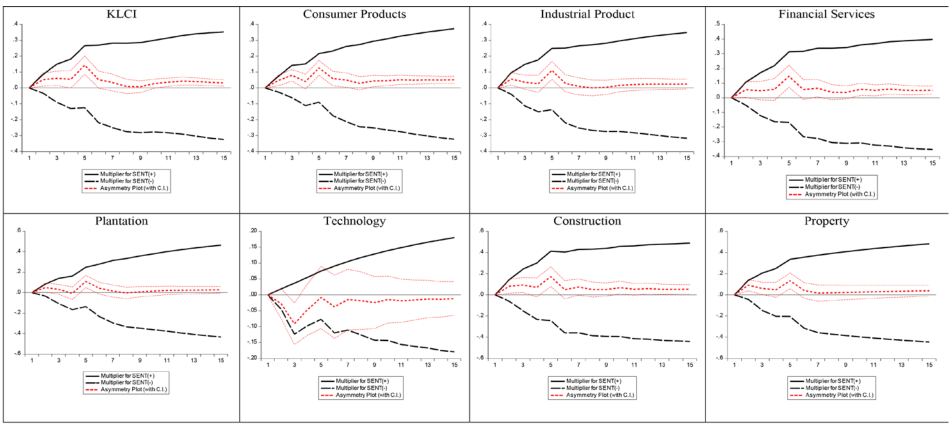

Figure 4: Asymmetric dynamic multiplier graphs

To validate our estimation, we also introduce a battery of diagnostic tests as shown in the lower panel of Table 6. From these diagnostics, we found that our optimum models are fit as indicated by the high estimates of adjusted R^2. Next, the functional form corrects specifications, and the absence of serial correlation are confirmed by the insignificant estimates attached to Functional RESET and Serial (LM), respectively. As depicted by the cumulative sum (CUMSUM) graphs in Figure 3, the parameters of our estimated models are statistically stable. Consequently, our empirical results are both valid and efficient, satisfying the fundamental requirement of stable parameters and free from serial correlation, in accordance with the criteria set by Pesaran et al. (2001). Nonetheless, we witnessed the issues of normality and heteroskedasticity in some of our estimated models. In practice, time series data often exhibit non-normal behaviour. As emphasised by Saqib et al. (2021), Pesaran et al. (2001) assert that ARDL (and NARDL) models only necessitate autocorrelation-free and statistically stable models. Since the presence of heteroskedasticity and outliers violate the assumption of ordinary least square, nonlinear models are preferred in such circumstances (Wilcox & Keselman, 2004). Additionally, Kriskkumar et al. (2022) underscore the flexibility of NARDL approach to model the relationship between variables under the presence of nonlinearities.

CONCLUSION AND POLICY IMPLICATIONS

Global events have significantly influenced Malaysia's financial market over the past three decades. Amid these events, market sentiment has emerged as a crucial factor that affects domestic investors' decisions and stock price expectations. This study aims to shed light on this relationship by constructing a sentiment index using PCA and analysing its influence on sectoral stock prices using NARDL modelling. To construct the sentiment index (SENT), we employed PCA on a dataset spanning 1996 to 2019. Subsequent NARDL modelling allows us to investigate both the short- and long-term asymmetric effects of optimistic and pessimistic sentiments on different sectoral stock indexes.

Our findings provide valuable insights into the existing literature. First, the constructed sentiment index proves to be a significant determinant of stock price movements during both bullish (e.g., 1996, 1999/2000, 2006/2007, 2010–2015, 2017/2018) and bearish periods (e.g., Asia Financial Crisis 1998, Dot-com Crisis 2001, Global Financial Crisis 2009). Notably, this effect is evident in the large-cap KLCI and its sub-sectors, such as consumer products, industrial products, financial services, technology and property. However, weaker sentiment effects were observed in the plantation and construction sectors. This finding indicates that investors' emotions may overpower rationality, a departure from the conventional EMH.

Second, the analysis reveals that the asymmetric effect of sentiment on stock prices is more pronounced in the long-run, with the exception of the technology sector. The short-term effects are limited because of regulatory constraints on short selling in Malaysia. In Malaysia, Regulated Short Selling (RSS) is only applicable to approved securities on the RSS list, which currently comprises 218 securities. Limits were also imposed to prevent excessive short selling activities. Third, the dynamic multiplier graphs suggest that sentiment effects tend to amplify after three months and stabilise after seven months for most sectors, including consumer products, industrial products, finance, plantation, construction and property stocks. However, technology stocks exhibit an overreaction to negative market sentiments, akin to the performance of tech stocks on the U.S. Wall Street since the new millennium.

Empirical evidence presents challenges to the EMH and highlights the relevance of behavioural finance in explaining stock price movements. While sentiment effects are mostly skewed towards positive adjustments, investors should not rely solely on sentiment-based decisions but also consider fundamental financial analysis. These findings serve as essential references for investors, regulators, and academics. Market participants such as individual traders and fund managers can enhance their portfolio investments and wealth creation strategies. Additionally, domestic authorities, such as Khazanah and the Employees' Provident Fund, can refer to this research to formulate improved hedging strategies and risk management policies. Finally, this study provides valuable insights into non-conventional equity analysis, particularly in the behavioural finance domain.

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NOTES

1. Short sales can result in losses far more than an investor's initial investment if the stock price climbs sharply higher than the price at which the short sale is made. Losses might be unlimited if the stock price climbs to astronomical heights.
2. The stock market was renamed as Bursa Malaysia in 2007, from previously known as Kuala Lumpur Stock Exchange (KLSE) that founded in 1964.
3. Malaysian Institute of Economic Research (MIER) has two important surveys on consumer and business. Since 1988, the Consumer Sentiment survey was conducted quarterly on a sample of over 1,000 households in Peninsular Malaysia to gauge consumer spending trends and sentiments. The Business Conditions Survey was initiated in 1987 and covers a sample of over 350 manufacturing businesses from 11 industries incorporated locally and foreign manufacturing concerns operating in Malaysia. Questions posed in the survey questionnaire are on key determinants such as production level, new order bookings, sales performances, inventory build-up and new job openings.

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