The predictive ability of consumer sentiment’s volatility to the Malaysian stock market’s volatility

Nathrah Yacob* and Nurul Shahnaz Mahdzan

Department of Banking and Finance, Faculty of Business and Accountancy, University of Malaya, 50603 Kuala Lumpur, Malaysia
Fax: 60378451975
Email: nathrahmy@yahoo.com
Email: n_shahnaz@um.edu.my
*Corresponding author

Abstract: In this paper, we examine the predictive ability of consumer sentiment volatility on the volatility of stock returns in Malaysia. We also investigate the relationship between volatility of consumer sentiment and volatility of stock market returns with a focus on the 2008 global financial crisis. The consumer sentiment index is derived from a national survey of 1,200 Malaysian households including a measurement of the level of consumers’ optimism or pessimism in regards to the economy. Although the surveys measure the general outlook of households in regards to the economy, the present paper provides distinct evidence that the consumer sentiment index is relevant to the Malaysian stock market behaviour. Results show that volatility of consumer sentiment index holds significant predictive power in explaining the behaviour of stock market volatility measured by GARCH (1,1). Findings also provide evidence of significant predictive power of the consumer sentiment volatility to stock market volatility during the 2008 global financial crisis.

Keywords: Asian; behavioural finance; emerging markets; investor sentiment; stock returns; volatility; Malaysia.

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Biographical notes: Nathrah Yacob is a PhD candidate at the University of Malaya in Kuala Lumpur, Malaysia. She is also an Academic at Taylor’s University, Subang Jaya with research interests in asset pricing and behavioural finance.

Nurul Shahnaz Mahdzan is an Academic at the Faculty of Business and Accountancy, University of Malaya, Kuala Lumpur and has published in several ISI-cited journals with interests in risk management, insurance and behavioural economics.
1 Introduction

For past decades, researchers have debated on the existence of stock market anomalies. The most worthy to mention is the vast empirical evidence of excess volatility that appears to challenge tenets of standard efficient market models (Shiller, 1981, 1987, 1990). The disparate evidence on anomalous behaviour of stock markets has obvious adverse implications for many parties. For one, lack of understanding on the causes of volatility may result in inaccurate investment strategies that may distort trading decisions of investors. Second, it may further lead to the formulation of substandard measures by regulators in the eradication of potential bubbles, hence adversely affecting performance and growth prospects of the overall economy.

Numerous research attempts have been made in search of the drivers to the anomalous performance, usually centring around macroeconomic fundamentals (e.g., Davis and Kutan, 2003; Officer, 1973; Schwert, 1989). Schwert (1989), for instance, analysed the relationship between stock market volatility and volatility of macroeconomic variables and found that although the stock market volatility correlated with aggregate leverage, it only weakly predicted volatility of stock movement. Davis and Kutan (2003) extended the influential works of Schwert (1989) by examining the relationship between stocks’ volatility and macroeconomic variables (inflation and real output) in 13 developed countries. Consistent with Schwert (1989), Davis and Kutan (2003) found marginal predictive power of the volatility of macroeconomic factors on stock market volatility in the USA as well as in other countries in their sample.

A growing strand of literature in the area of stock price volatility and anomalous behaviour has taken a turn from the perspective of traditional finance theories to that of behavioural finance. Olsen (1998) suggested that investors who make decisions under time pressure tend to immerse in inevitable emotions that ripple into more volatile stock price movements. Such reactions led to a conclusion that behavioural factors are plausible determinants of stock price volatility (Olsen, 1998). However, other authors have remained sceptical in accepting behavioural factors as a predictor of stock market movements, and prefer to rely on rational explanations.

Despite reservations in accepting non-fundamental behavioural factors as a predictor of stock market movements, studies that examine the impact of fundamental factors on stock market behaviour have continued to display inconclusive results. Akin to the observations of Schwert (1989), and Davis and Kutan (2003), weak relationship between stock market volatility and macroeconomic fundamentals are also manifested in the case of the Malaysian stock market, suggesting that there may be other factors underlying stock market movement (e.g., Angabini and Wasiuzzaman, 2010; Zakaria and Shamsuddin, 2012). Angabini and Wasiuzzaman (2010) suggest that this scenario may be explained by the over reaction of investor sentiment during high risk crisis periods.

Hence, the question remains as to whether Malaysian investors are easily manipulated by non-fundamental factors such as irrational behaviour in making their investment decisions. Uncertainties in the determinants of stock market volatility pose difficulties for international fund managers and investors to determine optimal investment strategies. This study is motivated by the need to examine non-fundamental factors that may influence the Malaysian stock market volatility, in particular, investor sentiment. Another factor that warrants an investigation on the Malaysian stock market is due to the fact that Bursa Malaysia is an order-driven market in which prices are determined by the
publication of orders to buy or sell shares via public investors, without the intermediation of market makers. Hence, the movement of stock prices is transparent to the sentiment of stock market participants. There also appears to be a gap in the literature in regards to linking consumer sentiment and stock market volatility particularly in the context of developing market. Therefore, this paper is an inception to mark the importance of the consumer sentiment index (CSI) in equity research of the emerging markets.

The objectives of this paper are two-fold. First, we examine the predictive value of consumer sentiment’s volatility to the volatility of stock returns, in consideration of the plausible impact of behavioural factors on stock market movements. Second, we investigate the relationship between volatility of consumer sentiment and volatility of stock market returns with a focus on the 2008 global financial crisis. In this regards, two variables are crucial to the study:

1. returns of the Kuala Lumpur composite index (KLCI) to measure volatility of the Malaysian stock market
2. CSI as a basis of measuring consumer sentiment volatility.

The rest of this paper is structured as follows. Section 2 provides a brief review of the literature on investor sentiment. Section 3 describes the data and methodology employed in the study. Section 4 presents the results and discussion. Finally, Section 5 concludes this paper.

2 Investor sentiment

The literature reveals inconsistencies in the exact definition of investors’ sentiment, ranging from vague statements about investors’ mistakes of over-reaction; to specific psychological biases that are model-specific (Shefrin, 2002). The proposition of noise trading by Black (1986) introduced a number of behavioural factors that are subsequently developed by other researchers (see for example, De Long et al., 1990, 1991; Campbell and Kyle, 1993). Shleifer (2000) defines investor sentiment as heuristic behaviour in which investment decisions are based on belief or rules of thumb rather than Bayesian rationality. Such notion appears to be applicable when investors’ preferences and beliefs are in agreement with psychological models rather than standard economic frameworks. Some researchers refer to investor sentiment as the inclination to trade on noise rather than information (Baker et al., 2012; Black, 1986; De Long et al., 1990; Shleifer and Vishny, 1997). Others refer to it as investors’ excessive pessimism (bearish) or optimism (bullish) towards the stock market’s current and future price (Brown and Cliff, 2004; Shefrin, 2008).

Measuring investor sentiment has been an encouraging research interest, perhaps partly due to historical events and empirical puzzles that seem to defy the traditional finance theory of market efficiency. Since most researchers do not even agree on a single definition of sentiment, there are even more contradictions in regards to its measurement. Dozens of sentiment measures have been proposed, ranging from direct survey measures of market analysts, to indirect measures derived from financial and stock market data (Baker et al., 2012; Brown and Cliff, 2005; Zouaoui et al., 2011).

In this study, we employ a proxy that is widely used to describe sentiments in the economy; that is, the CSI. It is a vital indicator of economic sentiment reported by the
central bank of Malaysia, Bank Negara Malaysia (BNM) (2013), in their quarterly economic reports. The sustained expansion in terms of consumer spending is reflected in the strong growth of consumer goods imports, sales of food and beverages, and credit card spending, all of which affect the nation’s gross domestic product (GDP). The CSI has also been termed interchangeably with the consumer confidence index (CCI), which has gained importance across the globe as a representation of investor sentiment in the stock market due to availability of the index in many countries. In recent years, an abundance of empirical studies have noted significant relationships between CCIs and stock returns in developed markets particularly during bear market conditions (Chen, 2011; Fisher and Statman, 2002; Hsu et al., 2011; Ho and Hung, 2012; Jansen and Nahuis, 2003; Schmeling, 2009). Findings of these studies thus provide a strong base for the adoption of the CSI as a proxy of investor sentiment in the context of this study.

3 Data and methodology

To meet the objectives of the study, Malaysian stock market data from year 2000 until 2012 was employed. Data was extracted from the KLCI comprising of the top 100 stocks in terms of market value capitalisation in Malaysia. The KLCI was selected as it is regarded as the best indicator of the Malaysian stock market and is well-known among foreign investors. It serves as a benchmark in measuring local stock market health and the performance of investment portfolios. In this respect, KLCI is also known to trigger the directions of investors’ sentiments. Stock market returns were calculated using the log prices of Kuala Lumpur Stock Exchange denoted as:

\[
RKLCI_t = \ln \left( \frac{KLCI_t}{KLCI_{t-1}} \right)
\]

where \( RKLCI_t \) is the KLCI returns in month \( t \), \( \ln \) is natural logarithm, \( KLCI_t \) is the KLCI price at the end of month \( t \) and \( KLCI_{t-1} \) is the KLCI price at the month of \( t-1 \).

A crucial variable in this study is the CSI published by Malaysian Institute of Economic Research (MIER) since 1988. This index is derived from surveys conducted quarterly on 1,200 households in the country. The survey poses questions regarding households’ current and expected financial position, short term employment outlook as well as their perspectives of the economic environment, and plans to purchase major durable goods. As the index is only available on quarterly basis, we interpolated the index into monthly intervals to maintain consistency with other variables. The data was interpolated using the cubic spline interpolation method. Cubic spline interpolation estimates values with a mathematical function with the advantage to minimise overall surface curvature, resulting in a smooth surface that passes exactly through the input points. It is a method that is popular among economists in the treatment of inconsistent frequency of financial data.

4 Results and discussion

The first part of the analyses involved the analysis of co-movement between the interpolated CSI and the movement of KLCI from 2000 to 2012. The volatility of KLCI
returns and consumer sentiment indices were modelled with the autoregressive conditional heteroscedasticity (ARCH) and the general autoregressive conditional heteroscedasticity (GARCH) modelling techniques and further analyses were conducted to determine the significance of investor sentiment in explaining volatility of stock returns during the study period. As noted in Figure 1, the CSI tumbled from 2008 until early 2009, suggesting a marked response during the 2008 global financial crisis.

**Figure 1** Monthly CSI post interpolation (see online version for colours)

![Figure 1 Monthly CSI post interpolation](image)

**Figure 2** The performance of Kuala Lumpur Stock Exchange (2000–2012) (see online version for colours)

![Figure 2 The performance of Kuala Lumpur Stock Exchange](image)

The Malaysian stock market behaviour appears to be aligned with the mortgage and banking crisis that began in the USA in early 2007 which further led to a collapse in the real equity market ending in February 2009 (Bartram and Bodnar, 2009). In Figure 2, it can be noted the KLCI declined from its highest point of 1,445 in December 2007 to its lowest point of 864 at the end of 2008. Technically, the co-movement, measured by the Spearman rank order correlation is significantly positive at 0.24. This generally suggests that the CSI follows closely with the movement of Bursa Malaysia’s leading stock market
indicator. Hence, this finding justifies the adoption of CSI in representing investor sentiment since presently there is no direct measurement for it in regards to Malaysian’s stock market.

4.1 Modelling volatility of CSI and stock market returns

As can be observed from Figure 3, the volatility during certain periods was higher than others, suggesting that the expected value of the magnitude of the disturbance term was greater at certain points. This is evident from a unit root test showing non-stationary of means and variance of the CSI data [test that are conducted are the Augmented Dickey-Fueller (ADF) and Phillips Perron (PP) tests at first level differences].

Figure 3 The conditional variance series for GARCH(1,1) (see online version for colours)

Figure 3 shows that there was a distinct behaviour between mid-2007 and early 2009 that corresponds to the period of the financial crisis in the USA. A significant spike in the middle of year 2008 is clearly noted, reflecting the perception of consumers to the current and expected future economy during the crisis period. The CSI dropped from 124.1 points in March 2007 to merely 69.72 points in 2009 January, signifying a drop of almost 50% in one year. This phenomenon supports the importance of examining the impact of the global crisis to the Malaysian stock market, as reflected in the second objective of this study. For this purpose, we segregate the analyses into two parts:

1. the entire period of study (2000 to 2012)
2. the period of the 2008 global financial crisis.

In line with the objective of this paper, the volatility of consumer sentiment index (VCSI) was modelled with the best possible tool. Apart from the justification of employing ARCH or GARCH as the standard tools to model volatility, the interpolated CSI seemed to post a non-constant variance of the disturbance term. To examine the impact of CSI’s volatility on Malaysian’s stock market, we began the analysis by modelling the conditional heteroscedasticity of the variance. As it is crucial to check the presence of ARCH effects, we employed the Breusch-Pagan test, testing the null hypothesis that the variances were homoscedastic, $\gamma_0 = \gamma_1 = \gamma_2 = \ldots = \gamma_4$. The resulting test statistics followed a $\chi^2$ distribution with $q$ degrees of freedom and produced results of 11.28 which were
highly significant. Thus, the hypothesis was rejected and suggested evidence of an ARCH(1) process. The details of the autoregressive heteroscedasticity order were provided by specific tests of ARCH (Engle, 1982). Engle’s idea starts from the notion that the variance of residuals ($\sigma^2$) should be allowed to depend on history and possess heteroscedasticity. In fact, the conditional variance can depend not only on one lagged realisation but can be more than one. For example, the ARCH(1) process will be:

$$Y_t = \alpha + \beta X_t + u_t$$  \hspace{1cm} (2)

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

$$\sigma_t^2 = \gamma_0 + \gamma_1 \sigma_{t-1}^2$$  \hspace{1cm} (3)

The ARCH(1) model shows that when a big shock occurs at period $t-1$, it is more likely that the value of $u_t$ will be bigger. Nevertheless, the conditional variable may depend not only on one lagged realisation for each case producing a different ARCH process. In general ARCH(q) process is given by:

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + ... + \gamma_q u_{t-q}^2$$

$$= \gamma_0 + \sum_{j=1}^{q} \gamma_j u_{t-j}^2$$  \hspace{1cm} (4)

The next step was to observe whether there was a higher-order ARCH effect, hence, a Breusch-Pagan test was re-conducted with an order of 2 and 3 as the $q$-term. The results show that the $\chi^2$ is 3.12 and is significant at the 10% level. However, the ARCH effect seemed to have disappeared at the higher order, $q > 2$. Therefore, the CSI suffers from the presence of autoregressive heteroscedasticity up to ARCH(2).

As it is common to measure conditional volatility of stock returns in the Malaysian stock market with GARCH(1,1) (see for example, Angabini and Wasiuzzaman, 2010, 2011; Albaity and Shanmugan, 2012; Law, 2006; Lim, 2008; Zakaria and Shamsuddin, 2012), there is a possibility that the CSI suffers from a similar effect. We therefore include the modelling of the GARCH effect which takes into account the lagged conditional variance terms following Bollerslev (1986). The general form of GARCH(p,q) takes on the following form:

$$Y_t = \alpha + \beta X_t + u_t$$

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

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

According to the above model, the value of the variance scaling parameter $h_{t-1}$ depends both on the past values of shocks and on the past value of itself. In order to estimate a simple GARCH(1,1) model, based on the assumption that the mean equation of CSI follows an AR(1) process, the mean specification is estimated by:

$$CSI_t = 6.227 + 0.943CSI_{t-1} + u_t$$  \hspace{1cm} (6)
After 18 iterations to reach convergence in the GARCH(1,1) estimation, the model can be written as:

\[ Y_t = 7.326 + 0.939Y_{t-1} + u_t \]

where \( u_t \sim iid \ N(0, h_t) \) \hspace{2cm} (7)

\[ h_t = 0.924 + 0.217h_{t-1} + 0.0874u_{t-1}^2 \] \hspace{2cm} (8)

Series of ARCH(2) and GARCH(1,1) are plotted together and the results are shown in Figure 4.

**Figure 4** Comparison of ARCH(2) and GARCH(1,1)

We observed that the two series were similar, suggesting that GARCH(1,1) captured a higher order of ARCH hence justifying the estimation of GARCH(1,1) to capture the VCSI. We then computed the LM statistic to detect whether the effect of GARCH was left in the model. The results illustrated that the LM test did not obligate any significant effect of GARCH presence with insignificant \( R^2 \) of 1.486, thus, failing to reject the hypothesis of homocedasticity of the variance.

The next step was to examine the relationship between CSI and the underlying causes of the stock market volatility. In this paper, we provide an empirical investigation of the links between VCSI and volatility of stock market returns. As the conditional volatility of the consumer sentiment was modelled as GARCH(1,1), it was crucial to determine the best fit tool to model the conditional volatility of KLCI returns. It is well-known that most macroeconomic and financial data series are trended and therefore are in most cases non-stationary. We employed the ADF and PP’s unit root tests with or without intercept and trends both at levels. The null hypothesis stating that returns of KLCI are non-stationary is significantly rejected at the 1% level, as shown in Table 1.

On the contrary, the results of the tests in the levels of CSI clearly pointed to the presence of unit root in all cases. However, the first differences of the CSI series removed non-stationary components in all cases and rejected the null hypothesis of non-stationarity; thus, suggesting that the series were integrated at order one (I(1)).
To support the modelling of volatility of the Kuala Lumpur composite index (VKLCI) with the ARCH or GARCH models, the daily returns of the KLCI are plotted in Figure 5. The chart indicates that there are certain periods that display higher volatility than others. Volatility clustering is obvious during the early years of 2000 to 2001, as well as in 2008 during the global financial crisis.

### Table 1

Unit root tests with PP and ADF for KLCI returns and CSI

<table>
<thead>
<tr>
<th></th>
<th>PP KLCI returns</th>
<th>PP CSI</th>
<th>ADF KLCI returns</th>
<th>ADF CSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-10.914***</td>
<td>-2.69</td>
<td>-10.826***</td>
<td>-2.186</td>
</tr>
<tr>
<td>Trend and intercept</td>
<td>-10.98***</td>
<td>-2.62</td>
<td>-10.939***</td>
<td>-2.124</td>
</tr>
<tr>
<td>None</td>
<td>-10.91***</td>
<td>-0.04</td>
<td>-10.807***</td>
<td>-0.037</td>
</tr>
</tbody>
</table>

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

### Figure 5

Returns of KLCI from 2000–2012 (daily frequency) (see online version for colours)

Meanwhile, Figure 6 shows that although the data is in monthly frequency, we can still observe sub-periods of high and low volatility during the entire period. The presence of volatility clustering during the global financial crisis in year 2008 to 2009 is especially noted. Results of the study reinforce the importance of examining investor sentiment on stock market volatility during the 2008 global financial crisis.

There is a possibility of an ARCH effect characterised in the series. The conditional volatility of KLCI returns were modelled as GARCH(1,1) for daily frequency from previous studies (e.g., Angabini and Wasiuzzaman, 2010) hence, we attempted to model the conditional volatility using ARCH and GARCH models. Using the Breusch-Pagan-Godfrey test of ARCH presence, ARCH(2) produced a $R^2$ of 255.07 which was significantly higher than ARCH(1)’s $R^2$ of 251.45. These findings conclude that there is presence of heteroskedasticity or ARCH effects in returns of KLCI, at a higher order; therefore, it is better to estimate the GARCH model due to easier estimation and to obtain the least possible loss of the degree of freedom (Asteriou and Hall, 2007). The GARCH(1,1) estimation took 346 iterations to reach convergence. Finally, we checked the presence of heteroscedasticity using the LM statistics and found an insignificant $R^2$ of 2.659. As a result, we failed to reject the null hypothesis of no ARCH
The predictive ability of consumer sentiment’s volatility

469

In conclusion, the GARCH(1,1) was found to be the best model to capture the volatility of KLCI returns, consistent with the findings of Zakaria and Shamsuddin (2012). Nonetheless, in order to maintain consistency of the CSI frequency used in this paper, KLCI returns with monthly frequency are considered for further tests.

Figure 6  Returns of KLCI from 2000–2012 (monthly frequency) (see online version for colours)

4.2 Structural breaks

The first and second objectives of this study involve the examination of the relationship and predictive power of consumer sentiment to the volatility of stock market. First, data of the entire period of study was analysed, and we further extracted data that fell during the period of the global financial crisis, as determined by structural breaks. In doing so, the volatility of KLCI was tested for structural breaks as to identify the episodes of unusual volatility during the 2008 global crisis.

There are a number of methodologies to determine structural breaks, including one that was proposed by Chow (1960). This classic test requires estimation of two sub periods’ models where the equality of the periods’ are tested using F-statistics. However, one of the disadvantages of this method is that the break date must be known a priori. Recently, more effective methodologies have been introduced where multiple structural breaks can be detected without a prior knowledge of the dates. One of the methods is the Bai-Perron (Bai and Perron, 1998, 2003a, 2003b) multiple structural test that allows multiple unknown breakpoints. In this analysis, the double maximum test is selected where the null hypothesis of no structural breaks against an unknown number of breaks.

The test uses equal weights version which estimates the break points obtained using global maximisation of the sum of squared residuals. This method requires the errors to be serially uncorrelated. Therefore, in order to construct the optimal bandwidth or heteroscedasticity and autocorrelation consistent (HAC) estimator, each element of the vector was estimated with quadratic spectral kernel with AR(1). As the residuals were serially uncorrelated, the optimal trimming was selected at $\epsilon = 0.15$ where the maximum breaks was set at 5. The results are shown in Table 2.
The results show five significant structural breaks from year 2000 to 2012 which are consistent with number of stock market crashes and financial crisis that occurred during the period. The crises include the Dot.com bubble in 2001 which observed the collapse of many internet-based companies in the USA as well as in Malaysia. In addition, the 9-11 attacks in US worsened the situation. Another structural break where higher volatilities was found was in 2008 – reflecting the global financial crisis originating from the USA. In accordance to Bai-Perron’s structural test, the significant period which is consistent with the 2008 global financial crisis is from January 2007 to February 2010, and lasted for a period of 38 months.

Table 2  
Bai-Perron’s structural break test, for entire period of study versus 2008 global financial crisis

<table>
<thead>
<tr>
<th>Breaks</th>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. error</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000M04–2002M01</td>
<td>C</td>
<td>0.007***</td>
<td>0.00022</td>
<td>32.92477</td>
</tr>
<tr>
<td>2002M02–2004M07</td>
<td>C</td>
<td>0.004***</td>
<td>0.000234</td>
<td>17.69586</td>
</tr>
<tr>
<td>2004M08–2006M12</td>
<td>C</td>
<td>0.003***</td>
<td>0.000165</td>
<td>15.81902</td>
</tr>
<tr>
<td>2007M01–2010M02</td>
<td>C</td>
<td>0.006***</td>
<td>0.000307</td>
<td>18.42219</td>
</tr>
<tr>
<td>2010M03–2012M12</td>
<td>C</td>
<td>0.0020***</td>
<td>0.000364</td>
<td>8.077677</td>
</tr>
</tbody>
</table>

R-squared 0.485513  Mean dependent var. 0.004409
Adjusted R-squared 0.471608  S.D. dependent var. 0.002341
S.E. of regression 0.001702  Akaike info criterion –9.882037
Sum squared resid. 0.000429  Schwarz criterion –9.783003
Log likelihood 760.9758  Hannan-Quinn criter. –9.841807
F-statistic 34.91632  Durbin-Watson stat 1.994798
Prob (F-statistic) 0

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

4.3 The nexus between CSI and the stock market volatility

It is well-known that financial data are mostly non-stationary in nature. As suggested by Engle and Granger (1987), there is a possibility that the combinations of two or more non-stationary series may cointegrate in the long run, suggesting a long run equilibrium. In order to check for cointegration among the variables, VCSI and VKLCI were tested with Johansen system cointegration test. However, prior to the cointegration test, it was crucial to exercise a common procedure in choosing the optimal lag length which involved estimating the VAR model that includes all variables in levels. The selection of lags was automatically done by Eviews 8 where the minimum value of selection criterion was determined. The results are exhibited in Table 3 where the minimum values are marked with an asterisk (*) denoting significance at the 5% level.

Owing to the limited number of samples during the global financial crisis, the possible lags were confined to maximum of 8 lags. Lutkepohl (2005) argued that each criterion has its own advantage and suggested that the final prediction error (FPE) is a good tool for forecasting when the series are stationary hence the process is stable. The Akaike’s information criterion (AIC) and FPE criterion are asymptotically equivalent in finite samples. However, the Schwarz information Criterion (SC) and the Hannan-Quinn
criterion (HC) proved to be consistent as they have the ability to correctly choose the order for a large sample. From Table 3, we can observe that the SC criterion suggests lag 4 as the optimal lag shown by its consistency in establishing the lags significance for the whole period of study, whilst lag 1 is suggested for the period of the global financial crisis.

Table 3  
Lag order selection criteria for CSI and VKLCI model of relationship for entire period of study versus 2008 global financial crisis

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AIC</td>
<td>SC</td>
</tr>
<tr>
<td>0</td>
<td>−15.95499</td>
<td>−15.91336</td>
</tr>
<tr>
<td>1</td>
<td>−19.64676</td>
<td>−19.52186</td>
</tr>
<tr>
<td>6</td>
<td>−21.70433</td>
<td>−21.16312</td>
</tr>
<tr>
<td>9</td>
<td>−21.77846*</td>
<td>−20.98746</td>
</tr>
<tr>
<td>10</td>
<td>−21.75179</td>
<td>−20.87753</td>
</tr>
<tr>
<td>11</td>
<td>−21.71649</td>
<td>−20.75897</td>
</tr>
<tr>
<td>12</td>
<td>−1.77068</td>
<td>−20.7299</td>
</tr>
</tbody>
</table>

Note: Symbol * denotes 5% significance level.

Post lag selection, the appropriate models were selected with regards to the deterministic components in the multivariate system. An important aspect in the formulation of the dynamic model was to determine whether the intercept and/or a trend should enter the short run model, long run model, or both models. In general, five distinct models were considered. Model 3 had an intercept in CE and VAR, with no trends in CE and VAR. In this case, there were no linear trends in the levels of the data but we allowed both specifications to drift around an intercept. In this case, it is assumed that the intercept in the CE is cancelled out by the intercept in the VAR, leaving just one intercept in the short run model.

Table 4  
The number of cointegrating models suggested by Johansen test for entire period of study versus 2008 global financial crisis

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Year 2000–2012</th>
<th>2008 global financial crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max eigen</td>
<td>Trace</td>
</tr>
<tr>
<td>r = 0</td>
<td>0.0914**</td>
<td>0.0914**</td>
</tr>
<tr>
<td>r ≤ 1</td>
<td>0.0212</td>
<td>0.0212</td>
</tr>
<tr>
<td>Number of CE</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: ** denotes 5% Critical values for the indicator of cointegrating equation based on MacKinnon-Haug-Michelis (1999) test.
Results from the Johansen cointegration test in Table 4 suggest a long-term equilibrium between all variables, which are hence cointegrated. The table summarises the results from Johansen test of cointegration. Results are given in two types of tests, namely, the trace statistic and maximum eigenvalue.

From Table 4, we can observe that both models hold one cointegrating equation as suggested by the trace statistic and maximum eigenvalue. The Johansen test of cointegration suggests that the variables are cointegrated, by definition, $\hat{u}_t \sim I(0)$. Thus, the relationship between VCSI and VKLCI has the advantage of including both long run and short run information. The relationship can be expressed with an error correction model, specified as below:

$$
\Delta Y_t = \alpha_0 + \beta_1 \Delta x_t - \pi \hat{u}_{t-1} + Y_t
$$

In this model, $\beta_1$ is the impact multiplier (the short run effect) that measures the immediate impact of a change in $x_t$ on $Y_t$. On the other hand, $\pi$ is the feedback effect, or the adjustment effect, and shows how much of disequilibrium is being corrected. From equation (9), $\hat{u}_{t-1} = Y_{t-1} - \hat{\beta}_1 - \hat{\beta}_2 x_{t-1}$, $\hat{\beta}_2$ is the long run response being estimated.

The long run effect is given when the model is in equilibrium whereby:

$$
Y_t = \beta_0 + \beta_1 X_t^*
$$

And it is assumed that,

$$
X_t^* X_t = X_{t,1} = ... = X_{t-p}
$$

Thus, it is given by:

$$
Y_t = \alpha_0 + \alpha_1 Y_t + \gamma_0 X_t^* + \gamma_1 X_t^* + \mu_t
$$

(12)

$$
Y_t (1-\alpha_1) = \alpha_0 + (\gamma_0 + \gamma_1) X_t^* + \mu_t
$$

(13)

$$
Y_t = \frac{\alpha_0}{1-\alpha_1} + \frac{\gamma_0 + \gamma_1}{1-\alpha_1} X_t^* + \mu_t
$$

(14)

$$
Y_t = \beta_0 + \beta_1 X_t^* \mu_t
$$

(15)

Therefore, the long run elasticity between $Y$ and $X$ is captured by $\beta_1 = (\gamma_0 + \gamma_1)/(1-\alpha_1)$.

The most important part of this equation is the interpretation of $\pi$ from equation (9). It tells how much of the equilibrium is corrected. The cointegrating equation where volatility is the dependent variable is formed and the output is shown in Table 4.

The results of the ECM as shown in Panel A reveal an error coefficient of 0.0283 which means that 2.83% of the adjustment takes place each period. The coefficient is significant and has negative value consistent with the assumption that $\gamma_1 < 1$, in order for the short run model to converge to a long run solution. Results presented in Table 4 indicate that there is a long run causality relationship between VCSI and volatility of the VKLCI for the whole period of study.
In addition to long run equilibrium, a short run relationship can also be observed from the output in Table 4 where the lagged difference of CPI is tested by WALD coefficient restriction test. The calculated $\chi^2$ yields a value of 33.50, significant at the 1% level. Therefore, the hypothesis that there is no short term relationship between VCSI and VKLCI is rejected. VCSI at lags 3 and 4 yield significant coefficient, suggesting that the consumer sentiment is able to predict the volatility of the Malaysian stock market three to four months in advance. The model was also checked for normality, serial correlation and presence of heteroscedasticity. The Durbin-Watson as well as the LM test consistently rejected the null hypothesis of a serial correlation in the residuals. While the model is free from the presence of heteroscedasticity, the distribution of data is of non-normality as suggested by the Jarque-Bera test result. This is, by far, the best fit model that identified the long run as well as short run dynamic relationships between the volatility of consumer sentiment and the volatility of KLCI measured from year 2000 until 2012.

Table 5  Cointegrating model with long run and short run dynamics between VCSI and VKLCI for entire period of study versus 2008 global financial crisis

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>Coefficient</td>
<td>p (value)</td>
<td>Variables</td>
</tr>
<tr>
<td>$\pi$</td>
<td>-0.0283*</td>
<td>0.0794</td>
<td>$\pi$</td>
</tr>
<tr>
<td>$\Delta$VKLCI$_{t-1}$</td>
<td>-0.2325***</td>
<td>0.0037</td>
<td>$\Delta$VKLCI$_{t-1}$</td>
</tr>
<tr>
<td>$\Delta$VKLCI$_{t-2}$</td>
<td>-0.0938</td>
<td>0.2411</td>
<td>$\Delta$VCSI$_{t-1}$***</td>
</tr>
<tr>
<td>$\Delta$VKLCI$_{t-3}$</td>
<td>-0.0309</td>
<td>0.7</td>
<td></td>
</tr>
<tr>
<td>$\Delta$VKLCI$_{t-4}$</td>
<td>-0.1137</td>
<td>0.1376</td>
<td></td>
</tr>
<tr>
<td>$\Delta$VCSI$_{t-1}$</td>
<td>-0.0107</td>
<td>0.156</td>
<td></td>
</tr>
<tr>
<td>$\Delta$VCSI$_{t-2}$</td>
<td>-0.0014</td>
<td>0.9201</td>
<td></td>
</tr>
<tr>
<td>$\Delta$VCSI$_{t-3}$</td>
<td>0.0284**</td>
<td>0.0465</td>
<td></td>
</tr>
<tr>
<td>$\Delta$VCSI$_{t-4}$</td>
<td>-0.0248***</td>
<td>0.0022</td>
<td></td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.2423</td>
<td></td>
<td>R$^2$</td>
</tr>
<tr>
<td>Adj R$^2$</td>
<td>0.1933</td>
<td></td>
<td>Adj R$^2$</td>
</tr>
<tr>
<td>F-stat</td>
<td>4.94***</td>
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<td>F-stat</td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>2.12</td>
<td></td>
<td>Durbin-Watson</td>
</tr>
</tbody>
</table>

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

Next, in order to meet the second objective, data was constrained to include only the months surrounding the global financial crisis as discussed in Section 4.2. Results are shown in Panel B of Table 4, indicating that 40.64% of error correction takes place every month until they cointegrate in the long run. The long run coefficient is noticeably more significant during the global financial crisis as opposed to the average period of year 2000 to 2012 ($\pi = 0.4064$ vs. $\pi = 0.0283$). On the other hand, in short run dynamics, VCSI is able to predict VKLCI as early as a month in advance. The relationship between VCSI and VKLCI is adverse in nature, suggesting that the higher the sentiment of investors, the less volatile of the stock market. In other words, low sentiment of investors increases stock market volatility. This finding is consistent with previous studies of Lee et al. (2002), and Verma and Verma (2007).
5 Conclusions

It is noteworthy that the volatility of the leading stock market indicator, KLCI, corresponds to the volatility of Malaysian consumer sentiment. This study suggests that generally, consumers are lagging in making their investment decisions. The act of spending activity is withheld until they are fully confident of the overall shape of the economy, which, according to results of the study, takes at least three months for investors to pool their resources and confidently invest in equities.

During financial crisis, however, volatility of consumer sentiment significantly causes the movement of volatility of stock returns as a result of instantaneous reduction in consumer spending. From a vantage point of the stock market, the behaviour of stock prices typically corresponds to the volatility of the real consumer sentiment and is able to predict stock price movement. The findings of the current research play significant role to academics, practitioners and policy makers in justifying the importance of investors' sentiment behaviours in stock market environment, particularly, in the volatility of stock returns. The evidence suggests that despite its typical usage as a measurement of household expectations of the economy in general, the CSI is also the closest proxy to measure the sentiment of investors in the Malaysian stock market, consistent with past researches.

Theoretically, it is well documented that when stock markets are efficient, no factor can explain or predict their movements except for non-fundamental variables. From the viewpoint of behavioural finance, non-fundamental factors are plausible determinants in asset pricing, mainly due to the correlated trading activity of unpredictable noise traders. The behaviour of noise traders will lead to difficulties in diversifying away from investment risk. From the findings of this study, it is apparent that investor sentiment succeeds in explaining stock market volatility. Thus, it can be concluded that the Malaysian stock market is, to a certain extent, inefficient and that there are opportunities of outperforming the market and earning abnormal returns on investments.

References


The predictive ability of consumer sentiment’s volatility


**Notes**

1 Previously known as Kuala Lumpur Stock Exchange.