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# **Does consumer sentiment predict consumer spending in Malaysia? an autoregressive distributed lag (ARDL) approach**

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20 January 2016

Online at <https://mpra.ub.uni-muenchen.de/69769/>

MPRA Paper No. 69769, posted 29 Feb 2016 07:07 UTC

# **Does consumer sentiment predict consumer spending in Malaysia? an autoregressive distributed lag (ARDL) approach**

Nor azza Mohd Haniff<sup>1</sup> and Mansur Masih<sup>2</sup>

## **Abstract**

The purpose of this paper is to determine the nature of relationship between consumer sentiment and consumer spending in the Malaysian context. The autoregressive distributed lag (ARDL) methodology is employed to test this relationship, controlling for information in other financial and economic indicators. The stability of the functions is tested by CUSUM and CUSUMQ and no structural break was found. Overall, the results show that the Consumer Sentiment Index does not have any predictive value on consumer spending either in the short-run or in the long-run, although a cointegrating relationship exists between the variables.

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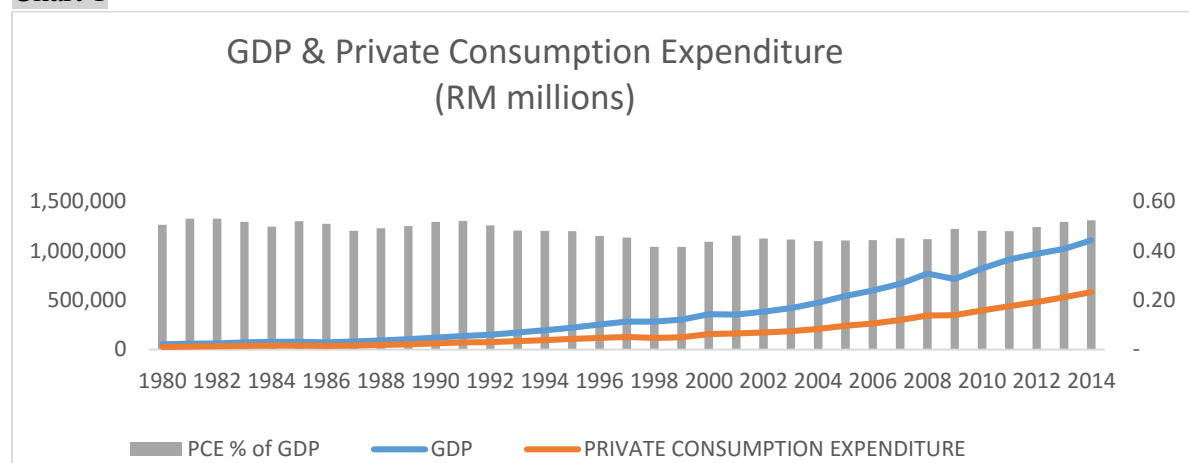
# Does consumer sentiment predict consumer spending in Malaysia? an autoregressive distributed lag (ARDL) approach

## 1. Introduction

Consumer spending, or private consumption expenditure, forms a large component of an economy of a country. This means that the state of the economy often rests upon the behaviours of the consumers. In Malaysia, the share of private consumption expenditure in the gross domestic product (GDP) was 52% in 2014, growing at an average annual rate of 10% since 1995 (see Chart 1).

Being a large part of aggregate demand, economic forecasters are interested in factors that influence or are able to predict consumer spending. One of these factors is consumer sentiment or consumer confidence. According to Alan Greenspan, consumer confidence is a key determinant of *near-term* economic growth (Greenspan, 2002). In the United States, consumer confidence is a leading indicator for the entire economy.

Chart 1



Data Source: IMF

Consumer sentiment is collected by surveys conducted in at least forty-five developed and emerging market economies and published ahead of consumer spending estimates (Curtin, 2007). These data are supposed to provide a link between consumer sentiment and near-term household economic decisions. Positive responses in the surveys indicate confidence about the current or future economic, business and household financial situation. In Europe, the consumer confidence indicator is an indispensable tool for monitoring the EU and the Euro area economies. In the U.S., consumer sentiment is included in the Conference Board's Leading Economic Index (LEI) whose cyclical turning points have historically occurred before those in the aggregate U.S. economic activity.<sup>3</sup>

<sup>3</sup> Detailed technical notes can be found on the Conference Board website <https://www.conference-board.org/data/bcicountry.cfm?cid=1> for the U.S. and on the European Commission's Economic and Financial Affairs website [http://ec.europa.eu/economy\\_finance/db\\_indicators/surveys/index\\_en.htm](http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm) for the EU.

Consumer sentiment has often been used as an indirect measure of investor sentiment for the purpose of investigating the influence of investor sentiment on stock returns. This proxy has increasingly been replaced by more direct measures of investor sentiment, such as investor surveys, the closed-end fund discount, the equity share in new issues and the dividend premium.<sup>4</sup> Compared to the consumer sentiment index, these newer measures provide results that are more broadly consistent with theories of investor sentiment and are better predictors of market returns. This is probably because consumer sentiment may react in a complex manner to unusual economic events, either more strongly or less than expected and may differ from investors' sentiment (Berry & Davey, 2004). Nonetheless, consumer sentiment indices are not meant to be replacements of other economic indicators but supplements to the latter in economic forecasting.

A breakdown in consumer confidence seems to accompany financial, economic and political crises. Following the Iraqi invasion of Kuwait, the University of Michigan's Consumer Sentiment Index fell an unprecedented 24.3 index points over three months to its lowest level since the 1981-1982 recession and an economic slowdown ensued (Carroll, Fuhrer, & Wilcox, 1994). In Malaysia, the Consumer Sentiment Index fell 30% between the second quarter of 2014 and the third quarter of 2015, and according to the Malaysian Institute of Economic Research, this is a result of political uncertainty (MIER, 2015). It is unclear whether a crisis of confidence the cause or the consequence of political uncertainty, economic slowdown or financial crisis, although what is clear is that it prolongs financial crises.

Reports have suggested that the 2007-2009 financial crisis resulted from a collapse in confidence.<sup>5</sup> There is some evidence to support this assertion. Using variance decompositions, Matsusaka and Sbordone found that consumer sentiment accounts for between 13 and 26 percent of the innovation variance of GNP (Matsusaka & Sbordone, 1995). Howrey found that consumer sentiment, either by itself or in conjunction with other economic indicators such as the spread between long- and short-term interest rates, the New York Stock Exchange composite price index, and the Conference Board Index of Leading Indicators, is a statistically significant predictor of the future rate of growth of real GDP. Specifically, the index produces an increase in the accuracy of one- to four-quarter-ahead forecasts of the probability of recession (Howrey, 2001).

Similarly, Haugh found that a confidence shock of four index points changes U.S. GNP by 0.2%, noting that it is not uncommon for confidence shocks to total 20 points over a few consecutive quarters. Confidence shocks accounted for 16% of the total effect of structural shocks to GNP in the 2001 recession (Haugh, 2005). This body of evidence suggests that economists ought to pay particular attention to confidence indicators when forecasting recessions.

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<sup>4</sup> See for instance Schmeling, 2008; Fisher & Statman, 2003; Jansen & Nahuis, 2002; Otoo, 1999; Charoenruek, 2005; Rashid, Hassan, & Ng, 2014; Baker & Wurgler, 2006

<sup>5</sup> Dees & Brinca (2011) quoted Joseph Stiglitz who said that the 2007-2009 "financial crisis springs from a catastrophic collapse in confidence". Similarly, Blanchard had said that a drop in confidence during the crisis led to a drop in demand and a major recession (Blanchard, 2009).

The main question in this paper is whether consumer sentiment is really a leading indicator of potential future changes in consumer spending in the near term and hence, changes in the macro economy. This paper attempts to answer this main question in the context of Malaysian household spending.

The rest of the paper is organized as follows. Section 2 describes the motivation behind this study and discusses some of the previous findings on the subject. Section 3 provides a literature review. Section 4 provides the theoretical background of consumer confidence and a discussion on private consumption expenditure. Section 5 describes the empirical framework used in this study and reports the results of the analyses. Section 6 contains the concluding remarks.

## 2. Motivation

As far as I am aware, there has not been any literature investigating this issue in the Malaysian context alone. Such an investigation is warranted because the accuracy of forecasts of almost all macroeconomic variables depends crucially on how accurately private consumption expenditure is forecasted (Wilcox, 2007). The quarterly Malaysian Consumer Sentiment Index (CSI) published by the Malaysian Institute of economic Research (MIER) is widely reported in the media upon release for the purpose explaining household spending intentions. MIER states that the CSI findings on consumer expectations are incorporated into their qualitative short-term economic outlook report.<sup>6</sup> The significance of the information provided by the CSI, whether it helps us to understand developments in the household sector and in the economy, remains unclear.

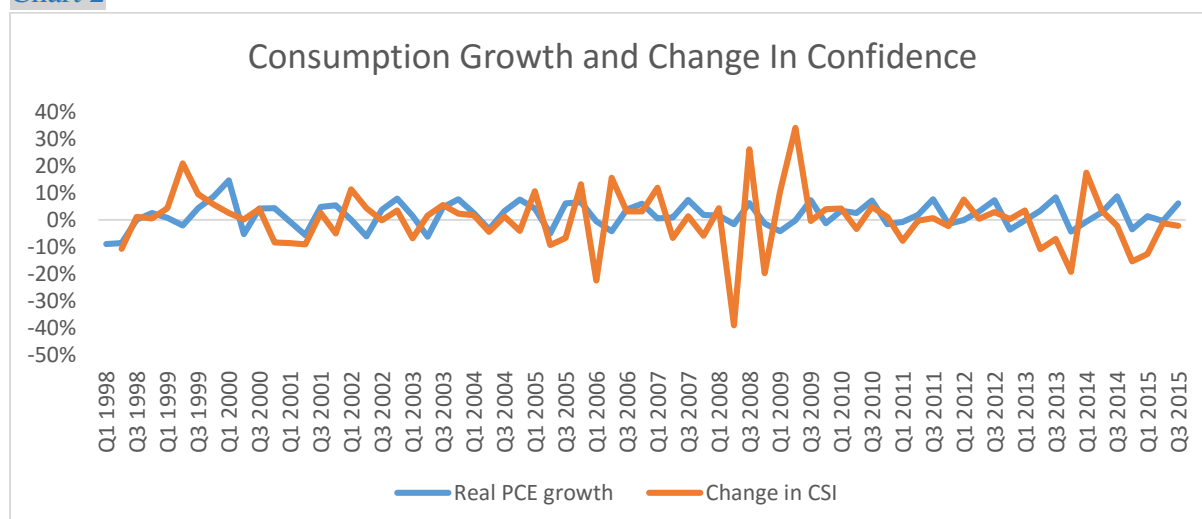
What is also unclear is whether the CSI is collecting information on consumer spending that is not already captured by other economic indicators. Does it provide additional information for the purpose of forecasting household expenditure? Is consumer sentiment statistically significant in predicting consumption when the current or past values of other variables that have been documented to account for changes in consumer spending are taken into consideration? Several authors have reported that consumer sentiment reduces forecast errors of models that include macroeconomic variables, while several others have reported otherwise.<sup>7</sup> If consumer spending represents more than half of GDP, then economic forecasting would require a good predictor of consumer spending.

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<sup>6</sup> This information is provided on the MIER website <https://www.mier.org.my/surveys/>

<sup>7</sup> Ludvigson (2004), Easaw & Heravi (2004) and Wilcox (2007) had reported an improvement in forecasting accuracy with the inclusion of consumer sentiment, whereas Smith (2009) and Claveria, Pons, & Ramos (2007) had either reported otherwise or that improvements in forecasting are significant in a limited number of cases.

Chart 2



*Data Source: IMF*

Furthermore, consumer sentiment is not only affected by economic events but also by non-economic events, as demonstrated by the fall in consumer sentiment following the Iraqi invasion of Kuwait. How does a change in consumer sentiment brought about by such a non-economic event relate to consumer spending decisions? A preliminary investigation finds that the correlation between the growth of real personal consumption expenditure and the change in CSI in Malaysia is 0.17 compared to 0.5 in the U.K., 0.42 in the EU and 0.24 in the U.S. (see Chart 2).<sup>8</sup> At least, consumer sentiment shows some co-movement with the Malaysian household spending in certain circumstances but not in all cases. Thus, as suggested by the Bank of England report and by Bram & Ludvigson (1998), it is important to consider the reasons behind changes in sentiment before assessing any impact on household spending.<sup>9</sup>

The purpose of this paper is to empirically assess the role of the CSI in explaining private consumption expenditure in Malaysia, statistically and economically, to explain the implications on macroeconomic policy and to present the possibilities for improvements, if necessary.

### 3. Literature review

In the United States, the University of Michigan's Index of Consumer Sentiment and the Conference Board's Consumer Confidence Index are the most widely followed measures of U.S. consumer confidence (Ludvigson, 2004). According to Barnes and Olivei (2013), there is a widespread consensus that the role of consumer sentiment in explaining consumption is small but statistically significant. Some authors have found that summary measures have some explanatory power for aggregate consumption behaviour, even when controlling for economic variables, but the impact is modest from an economic standpoint (Barnes & Olivei, 2013).

<sup>8</sup> See Dees & Brinca (2011) and Berry & Davey (2004)

<sup>9</sup> See "How Should We Think About Consumer Confidence" report by Berry & Davey (2004) for the Bank of England

The relationship between consumer confidence and consumer spending in developed countries including Europe and the U.S. has been substantiated in literature. Measures of consumer confidence have been found to be highly correlated with real consumption in the U.S. and in the Euro area. In the U.S., the correlation between real consumption growth and the change in consumer sentiment (measured by the University of Michigan Consumer Sentiment Index) is 0.28 when computed contemporaneously. In the Euro area, the correlation between confidence and consumption is the highest when confidence is lagged by one period (0.42) and remains large for higher lags (0.20 for a 2-period lag and 0.21 for a 4-period lag) (Dees & Brinca, 2011).

Another study found that the consumer sentiment index Granger causes future consumption with an average time lag of 4-5 months. The same study finds that the consumer sentiment index has more incremental predictive power for consumption of durables or non-durables, and that the index is not only useful as a predictor at the very short term but also for larger time horizons (Gelper, Aurelie, & Crux, 2007).

Howrey (2001) found that consumer sentiment, either by itself or in conjunction with other indicators, namely the spread between long and short term interest rates, the New York Stock Exchange composite price index, and the Conference Board Index of Leading Indicators, is a statistically significant predictor of the future rate of growth of real GDP. However, he found conflicting evidence on the significance of consumer sentiment in predicting personal consumption expenditure, depending on the use of either monthly data or quarterly data (Howrey, 2001).

Bram and Ludvigson (1998) found that lagged values of the Conference Board Consumer Confidence Index provide information about the future path of spending that is not captured by lagged values of the Michigan Index of Consumer Sentiment, labor income, stock prices, interest rates, or the spending category itself. They found that the superiority of the Conference Board Index for forecasting consumption appears to be related to the types of questions that make up the survey. The questions about job prospects in the respondent's area have the greatest predictive power. In contrast, the Michigan index's questions on buying conditions and financial conditions in the 1990's exhibit little predictive power. The authors recommended that policymakers pay close attention to the questions that generate the responses when there is a major shift in sentiment (Bram & Ludvigson, 1998).

On the other hand, although Kellstedt et al (2015) found that the Michigan's Index of Consumer Sentiment is a reliable predictor of consumer confidence and exhibits substantial face validity, it still falls short in terms of its predictive value with regard to spending on durable goods (Kellstedt, Linn, & Hannah, 2015).

Carroll et al (1994) found that lagged values of the Consumer Sentiment Index, taken on their own, explain about 14 percent of the variation in the growth of total real personal consumption expenditures over the post-1954 period but beyond that, it contributes little additional information on future path of spending (Carroll, Fuhrer, & Wilcox, 1994).

Given the various conflicting evidence, it is important to find out if the Malaysian CSI has any predictive value on the short-run and the long-run consumer spending in Malaysia.

For the purpose of this paper, following other research, I assume that the CSI is a good proxy of consumers' expectations about their economic environment and future spending and it follows that sentiment forecasts changes in spending and also causes them.

#### 4. Theoretical background on consumer sentiment and consumer spending

##### 4.1. Theoretical background

There are two points of view underpinning the link between consumer confidence and economic decisions. From a theoretical viewpoint, Milton Friedman's Permanent Income Hypothesis (PIH) plays a role in economic decisions. According to PIH, disposable income has two parts – permanent or expected income and transitory income.

The first part asserts that people have an expectation of what their long term expected average income would be and they would spend an amount of money consistent with this expectation. The second part refers to transitory changes in income due to one-time events and these have little effect on consumer spending. They will mainly affect savings. A negative transitory change would cause consumers to go into debt or use up past savings. Conversely, a positive transitory change would cause consumers to pay off their debt or add to their savings. Thus, PIH suggests that past values of consumer sentiment has no effect on future consumer spending (Dees & Brinca, 2011).

In reality, PIH does not hold in full due to distortions in the real economy, such as the credit crisis (Berry & Davey, 2004). In face of any uncertainty about future income, the consumer would decrease current consumption and build precautionary savings to face a drop in their income. Thus, the idea is that consumer confidence index might capture this sentiment and information about expected income and in turn, affect future consumer spending. The second part is from an empirical perspective, where the focus has been on finding a significant statistical relationship between consumer confidence and economic variables (Dees & Brinca, 2011).

According to George Katona, consumer spending depends on both their "ability and willingness to buy".<sup>10</sup> Ability refers to current income of consumers whereas willingness refers to discretionary purchases. This means that necessities such as food, healthcare and utilities are excluded from this definition. Discretionary purchases are those that can be postponed, are infrequent and large in value. In the U.S., they include items such as motor vehicles, homes and durable items. In less developed countries, discretionary purchases are less expensive nondurable items by the standards of advanced economies. What is considered discretionary in an advanced economy may not be discretionary in a less advanced economy. However, the principle remains the same. Discretionary purchases are items that are subject to expectations about future economic conditions because they dominate the cyclical changes in household consumption expenditure.

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<sup>10</sup> George Katona developed the first measures of consumer confidence in the late 1940s in order to incorporate empirical measures of expectations into model of of spending and saving behaviour (Curtin, 2007)



Apart from discretionary purchases and current income, there are other influences on consumer spending decisions. Consumers have greater financial latitude today than in the past and are able to time their spending decisions according to their present and future needs. This timing is more dependent on their expectations about future income, employment, interest rates and inflation and less dependent on past financial and economic situation. The disparity in economic development across countries determine the importance of expected income against the importance of various economic expectations. Consumers in advanced economies with wealth invested in financial assets and real estate are dependent on a broader range of expectations that affect their financial wealth, such as expected returns on assets, inflation, pension and healthcare entitlements compared to consumers in less developed economies, and so their spending decisions rest upon these expectations. (Curtin, 2007). Thus, consumer sentiment surveys are meaningful to the extent of their ability to capture expectations that affect future spending.

#### 4.2.Consumer Sentiment Index

Consumer sentiment is captured by surveys that ask a sample from the general population several qualitative questions. The surveys differ from country to country generally in respect of the reference period (past, present and/or expected changes) while the questions are similar (Curtin, 2007). The Malaysian Consumer Sentiments survey is conducted on a quarterly basis on a sample of over 1,200 households. The reference period is six months ahead. The questions asked in the survey to measure consumer sentiment are related to

- Current financial position/income
- Expected financial position/income in six months
- Expected change in employment in six months
- Expectations about general economic conditions such as inflation in six month
- Purchase plans for durables such as new and used car and house

A value above 100 indicates expected improvements in conditions. A value below 100 indicates a lack of confidence. A value of 100 indicates neutrality. The all-time high of 124.10 was recorded for the first quarter of 2007 while the record low of 70.20 was recorded for the third quarter of 2015.

#### 4.3.Consumer spending

The Department of Statistics conducted the Household Expenditure Survey in 2000, 2009 and 2014. Interviews of the population sample from the urban and rural areas throughout Malaysia were conducted over a twelve-month period for each of those years. Table 1 describes the Malaysian household spending by purpose. The data depict a shift in the pattern of household consumption. There has been a steady decline in durables such as furnishings, household equipment and maintenance from 5.9 percent in 2000 to 3.8 percent in 2014. The other substantial declines are in food and non-alcoholic beverages, healthcare, miscellaneous goods

and services and education. The percentage of household consumption spent on restaurants and hotels have seen a substantial increase from 5.8 percent in 2000 to 12.7 percent in 2014. If shifts in spending pattern are significant, they may affect the predictive value of the CSI on future consumer spending although a shift in consumption towards domestic demand would contribute to GDP growth.

**TABLE 1**

Household Consumption By Purpose	2000	2009	2014
	Percentage of Total Household Consumption		
Food and non-alcoholic beverages	24.1	20.3	18.9
Alcoholic beverages and tobacco	2.2	2.2	2.3
Clothing and footwear	3.5	3.4	3.5
Housing, water, electricity, gas and fuels	21.7	22.6	23.9
Furnishings, household equipment and maintenance	5.9	4.1	3.8
Health	2.1	1.3	1.6
Transport	12.6	14.9	14.6
Communications	4.9	5.6	5.3
Recreation and culture	4.3	4.6	4.9
Education	1.5	1.4	1.1
Restaurants and hotels	5.8	10.9	12.7
Miscellaneous goods and services	11.6	8.7	7.4

*Source: Department of Statistics, Malaysia*

## 5. Data and Methodology

### 5.1. Data

All time-series data analysed are for the period between the first quarter of 1998 and the third quarter of 2015 due to the fact that consumer sentiment surveys only began in 1998.

Consumer sentiment data are drawn directly from MIER's quarterly Consumer Sentiment Index on their website. Consumer spending or private consumption expenditure is the total spending by resident households domestically and abroad. Quarterly nominal data on or private consumption expenditure are sourced from the IMF database on Datastream and adjusted for inflation to derive real private consumption expenditure.

Other variables, such as interest rate and real household disposable income, which have empirically been noted to have predictive power over consumer spending are also included to

test whether consumer sentiment can stack up against other macroeconomic variables in predicting consumer spending.<sup>11</sup> All these variables are sourced from Datastream

Household disposable income is the sum of household final consumption expenditure and savings, net of income taxes. The quarterly data are adjusted for inflation to derive real disposable income.

The proxy for short-term interest rate is the monthly three-month Treasury bill rate, averaged over the three month period to obtain quarterly values. Quarterly disposable income data are adjusted for inflation to derive real disposable income.

Following research by Carroll, Fuhrer, & Wilcox (1994) and Ludvigson (2004) on consumer sentiment, I add to my model real stock prices. The proxy for real stock price is the KLCI. Quarterly data are adjusted for inflation to derive the real stock price index. The reason for the inclusion of real stock price is that researchers have argued that information contained in consumer survey data should be assessed relative to that contained in financial indicators. Financial indicators may contain much of the same information contained in consumer sentiment and have been found as such in previous research (Ludvigson, 2004).

## 5.2. Functional form of the model

The functional form of the model is given by

$$RPC = f(CSI, RDI, KLC, TBL)$$

Where

RPC= Real private consumption expenditure

CSI= Consumer Sentiment Index

RDI = Real household disposable income

KLC= Real KLCI

TBL= Three month averaged Treasury Bill rate

## 5.3. Regression model

In order to test the regression model, the following equation is applied

$$LRPC_t = \alpha_0 + \alpha_1 LCSI_t + \alpha_2 LRDI_t + \alpha_3 LKLC_t + \alpha_4 LTBL_t + e_t$$

## 5.4. Methodology

In order to test the long-run relationship and dynamic interactions between real consumer spending, consumer sentiment, real disposable income and the financial indicators, the autoregressive distributive lag (ARDL) approach by Pesaran and Pesaran (1997) and Pesaran, Shin,

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<sup>11</sup> See Carroll, Fuhrer, & Wilcox (1994), Ludvigson (2004), Dees & Brinca (2011),

& Smith, (2001) is employed. The reason for this is that unit root tests revealed that the variables to be used in the model are a mix of I(0) and I(1). In order to test for co-integration, the often-used Engle-Granger (1987) approach requires the variables to be integrated or order one.

An advantage of the ARDL method is that the variables are not required to be I(1) (Pesaran & Pesaran, 1997). Another advantage is that it can determine more efficient co-integration relationships even with small samples (Ghatak & Siddiki, 2001). In the case of the Johansen co-integration technique, it requires the use of large samples. Furthermore, unit root tests, such as Augmented Dickey Fuller and the Phillips Perron tests, can either lead to contradicting results or lead to the conclusion that the series has a unit root when indeed it is stationary with a one-time structural break (Perron, 1989). The ADRL approach avoids this problem.

Another problem that ARDL avoids is the number of choices that must be made such as the order of the VAR, the number of lags to be used, the number of endogenous and exogenous variables, and the treatment of deterministic elements. Estimation procedures are very sensitive to the method used to make these decisions and choices (Pahlavani et al, 2005).

An Error Correction Model (ECM) can also be drawn from the ARDL approach. This ECM allows drawing outcome for long run estimates unlike other traditional co-integration techniques. It contains short run adjustments and long run equilibrium without losing long run information (Pesaran & Shin, 1999).

The above advantages of the ARDL technique over other standard co-integration techniques justifies the application of ARDL approach to analyse the impact of consumer sentiment (CSI) on real private consumption expenditure (RPC), controlling for the variables real disposable income (RDI), real stock prices (KLC) and short-term interest rate (TBL).

The next step in the analysis is to test the null hypothesis of no co-integration ( $H_0: \delta_1 \delta_2 \delta_3 \delta_4 \delta_5 = 0$ ) against the alternative hypothesis that co-integration exists ( $H_1: \delta_1 \delta_2 \delta_3 \delta_4 \delta_5 \neq 0$ ) between all variables by using F-statistics. The F-test, which has a non-standard distribution, is considered on the lagged levels of the variables in determining whether a long-run relationship exists among them. In this regard, two bounds of critical values are generated. The lower bounds' critical values serve as benchmarks for the I(0) variables, while the upper bounds' critical values serve as benchmarks for the I(1) variables. According to the bounds test, co-integration exists if the computed F-statistic exceeds the upper bound critical value. If the computed F-statistic falls within the two bounds of critical values, the variables must be composed of level and first-differenced integrated series for the possibility of co-integration. Finally, if the F-statistic is below the lower critical value, it implies that there is no co-integration.

In the next step, short run and long run linkage is examined by using the error correction model (ECM). This approach to co-integration involves estimating the unrestricted error correction model version of the ARDL model for consumer spending and its determinants. By applying the ECM version of ARDL, the speed of adjustment back to the equilibrium will be determined in the third stage.

## 5.5. Error correction model

The error correction version of the ARDL (4, 4, 4, 4, 4,) model is as follows:

$$\begin{aligned}\Delta\text{IRPC}_t = & \alpha + \sum_{i=1}^4 \alpha \Delta\text{IRPC}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{ICSI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRDI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IKLC}_{t-i} \\ & + \sum_{i=1}^4 \alpha \Delta\text{ITBL}_{t-i} + \delta_1 \text{IRPC}_{t-1} + \delta_2 \text{ICSI}_{t-1} + \delta_3 \text{IRDI}_{t-1} + \delta_4 \text{IKLC}_{t-1} \\ & + \delta_5 \text{ITBL}_{t-1} + e_t\end{aligned}$$

$$\begin{aligned}\Delta\text{ICSI}_t = & \alpha + \sum_{i=1}^4 \alpha \Delta\text{ICSI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRPC}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRDI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IKLC}_{t-i} \\ & + \sum_{i=1}^4 \alpha \Delta\text{ITBL}_{t-i} + \delta_1 \text{ICSI}_{t-1} + \delta_2 \text{IRPC}_{t-1} + \delta_3 \text{IRDI}_{t-1} + \delta_4 \text{IKLC}_{t-1} \\ & + \delta_5 \text{ITBL}_{t-1} + e_t\end{aligned}$$

$$\begin{aligned}\Delta\text{IRDI}_t = & \alpha + \sum_{i=1}^4 \alpha \Delta\text{IRDI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRPC}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{ICSI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IKLC}_{t-i} \\ & + \sum_{i=1}^4 \alpha \Delta\text{ITBL}_{t-i} + \delta_1 \text{IRDI}_{t-1} + \delta_2 \text{IRPC}_{t-1} + \delta_3 \text{ICSI}_{t-1} + \delta_4 \text{IKLC}_{t-1} \\ & + \delta_5 \text{ITBL}_{t-1} + e_t\end{aligned}$$

$$\begin{aligned}\Delta\text{IKLC}_t = & \alpha + \sum_{i=1}^4 \alpha \Delta\text{IKLC}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRPC}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{ICSI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRDI}_{t-i} \\ & + \sum_{i=1}^4 \alpha \Delta\text{ITBL}_{t-i} + \delta_1 \text{IKLC}_{t-1} + \delta_2 \text{IRPC}_{t-1} + \delta_3 \text{ICSI}_{t-1} + \delta_4 \text{IRDI}_{t-1} \\ & + \delta_5 \text{ITBL}_{t-1} + e_t\end{aligned}$$

$$\begin{aligned}\Delta\text{ITBL}_t = & \alpha + \sum_{i=1}^4 \alpha \Delta\text{ITBL}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRPC}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{ICSI}_{t-i} + \sum_{i=1}^4 \alpha \Delta\text{IRDI}_{t-i} \\ & + \sum_{i=1}^4 \alpha \Delta\text{IKLC}_{t-i} + \delta_1 \text{ITBL}_{t-1} + \delta_2 \text{IRPC}_{t-1} + \delta_3 \text{ICSI}_{t-1} + \delta_4 \text{IRDI}_{t-1} \\ & + \delta_5 \text{IKLC}_{t-1} + e_t\end{aligned}$$

The hypothesis to be tested is the null of non-existence of a long-run relationship, defined by

H<sub>0</sub>:  $\delta_1 \delta_2 \delta_3 \delta_4 \delta_5 \delta_6 \delta_7 = 0$  against H<sub>1</sub>:  $\delta_1 \delta_2 \delta_3 \delta_4 \delta_5 \delta_6 \delta_7 \neq 0$

As discussed earlier, we use the following variables for our lead-lag analysis. All the variables are transformed into natural logarithms to achieve stationarity in variance.

I begin empirical testing with diagnostics tests of the data set which are treated as base for all other empirical tests. First, the stationarity of the variables is determined. In order to proceed

with co-integration tests, ideally, the variables should be I(1), meaning they are non-stationary in their level form and stationary in their first differenced form. The differenced form for each variable used is created by taking the difference of their log forms. For example,  $DLRPC = LRPC_t - LRPC_{t-1}$ .

## 5.6. Empirical Results and Discussions

Unit root tests were performed prior to proceeding to use the ARDL technique. This is to confirm that none of the variables are I(2), as such data will invalidate the ARDL methodology. The Augmented Dickey Fuller test and the Phillips-Perron (PP) test reveal that the variables are both I(1) and I(0). I ran an additional unit root test, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, but the results conflict with ADF and PP test results and so, I rely on the previous results to proceed with the ARDL methodology.

**TABLE: 2 Augmented Dickey Fuller (ADF) Test**

Variable	Test Statistic	Critical Value	Implication
Variables in Level Form			
LRPC	-5.7024	-3.4790	STATIONARY
LCSI	-3.1297	-3.4790	NON-STATIONARY
LRDI	-2.0936	-3.4790	NON-STATIONARY
LKLC	-4.1665	-3.4790	STATIONARY
LTBL	-3.2013	-3.4790	NON-STATIONARY
Variables in Differenced Form			
DRPC	-5.1957	-2.9069	STATIONARY
DCSI	-5.1412	-2.9069	STATIONARY
DRDI	-5.2897	-2.9069	STATIONARY
DKLC	-5.6955	-2.9069	STATIONARY
DTBL	-7.0387	-2.9069	STATIONARY

**TABLE 3: Philip-Perron (PP) Test**

Variable	Test Statistic	Critical Value	Implication
Variables in Level Form			
LRPC	-5.0836	-3.4739	STATIONARY
LCSI	-2.2941	-3.4739	NON-STATIONARY
LRDI	-3.0286	-3.4739	NON-STATIONARY
LKLC	-3.5520	-3.4739	STATIONARY
LTBL	-2.8181	-3.4739	NON-STATIONARY
Variables in Differenced Form			
DRPC	-15.8467	-2.9035	STATIONARY
DCSI	-11.2850	-2.9035	STATIONARY
DRDI	-8.7544	-2.9035	STATIONARY
DKLC	-13.6428	-2.9035	STATIONARY
DTBL	-10.2580	-2.9035	STATIONARY

TABLE 4: Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

Variable	Test Statistic	Critical Value	Implication
Variables in Level Form			
LRPC	.14059	.14877	STATIONARY
LCSI	.13471	.14877	STATIONARY
LRDI	.14311	.14877	STATIONARY
LKLC	.098257	.14877	STATIONARY
LTBL	.13340	.14877	STATIONARY
Variables in Differenced Form			
DRPC	.15256	.39892	STATIONARY
DCSI	.28539	.39892	STATIONARY
DRDI	.16252	.39892	STATIONARY
DKLC	.14697	.39892	STATIONARY
DTBL	.25280	.39892	STATIONARY

Next, I determine the vector autoregressive (VAR) order. This step is actually not necessary since the ARDL methodology find the lag order for each variable. According to the Schwatz (SBC) criterion, the optimal lag order is 4. SBC is an estimate of a function of the posterior probability of a model being true, under a certain Bayesian setup, so that a lower SBC means that the model is considered to be more likely to be the true model. It is a *consistent* model-estimator.

TABLE 5: VAR order Selection

	Choice Criteria
	SBC
Optimal order	4

The next step is conducting the bounds test for co-integration. The key assumption in the Bounds Testing methodology is that the errors of the unrestricted or conditional ECM must be serially independent. Diagnostic tests confirm that there the errors are serially independent.

The results in Table 5 indicate that there is a co-integrating relationship when the dependent variable is the short-term interest rate. The F-statistic (5.1589) is greater than the upper bound critical value of 3.805 at the 5% significance level. It can be concluded that there is a long-term theoretical relationship between real personal consumption, consumer sentiment, real household disposable income, the stock index and the three-month interest rate, ruling out the possibility of a spurious relationship. However, a co-integrating relationship does not reveal the short-run dynamics. The variables may still deviate from one another in the short-run. The short-run dynamics are estimated by the error correction model in the ARDL (ECM-ARDL).

TABLE 6: Bound Test for Co-integration (F Test)

Variables	F statistics	Critical Value Lower	Critical Value upper
DRPC	1.5061	2.649	3.805
DCSI	1.2442	2.649	3.805
DRDI	.65866	2.649	3.805
DKLC	2.0956	2.649	3.805
DTBL	5.1589*	2.649	3.805

Thus, the next step estimates the short-run elasticity of the variables with the error correction representation of the ARDL model. The error-correction (ECM[-1]) coefficient indicates the speed of adjustment to restore equilibrium in the dynamic model. The optimum lags are selected based on the the Schwartz Bayesian Criteria (SBC) because it will select a lower order of lags and hence, a more parsimonious model.

The ECM-ARDL indicates both the long run relationship between the variables and whether the variables are exogenous or endogenous. If the p-value of the ECM coefficient is less than the chosen 5% significance level, this indicates that the short-run deviation from equilibrium has a significant feedback effect on the endogenous variable. The results in Table 6 show that except for the variable real disposable income, all other variables are indicated as endogenous. The size of each of the ECM coefficients falls between -1 and 0, indicating there exists partial adjustment and that there is co-integration among the variables. A positive value would imply that the system moves away from equilibrium in the long-run, and a value of zero would indicate that a long-run equilibrium relationship does not exist.

These results indicate that real consumer spending, consumer sentiment, real stock index and the three-month interest rate are all dependent on real disposable income. Disposable income and interest rate have been found to be a statistically significant determinant of consumer spending in prior research.<sup>12</sup> The results here also indicate that disposable income predicts interest rate movements. Consumer sentiment is also determined by short-term interest rate, according to these results. This is a likely prediction as the central banks commonly look at consumer sentiment when determining interest rate changes. These results do not indicate, however, if real consumer spending is the most dependent variable. Thus, I would at this stage also refer to prior research findings which indicate that changes in consumer sentiment explain changes in real consumer spending in order to perform the next step of estimating short-run and long-run coefficients.

TABLE 7: Results of Error Correction Representation for the selected ARDL Model

Variables	Coefficient	Standard Error	T-statistics	P value
ECM (-1) dLRPC	-.32672	.044197	-7.3924	[.000]**
ECM (-1) dLCSI	-.54872	.10673	-5.1411	[.000]**
ECM (-1) dLRDI	-.14329	.090584	-1.5819	[.119]
ECM (-1) dLKLC	-.67786	.11088	-6.1132	[.000]**

<sup>12</sup> Macklem (1994) , Ludvigson (2004), Carroll, Fuhrer, & Wilcox (1994) , Dees & Brinca (2011)



ECM (-1) dLTBL	-.24647	.087822	-2.8065	[.007]**
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\*\* denotes significance at the 5% level

Table 7 depicts the short-run relationship between real consumer spending and all other variables. Results indicate that real disposable income and real stock index are both statistically significant in explaining the short-run changes in real consumer spending. In terms of economic significance, they are not particularly large, nor are they insignificant, with real disposable income having the larger positive effect on consumer spending.

Consumer sentiment, on the other hand, does not affect real consumer spending in the short-run. This actually contradicts the purpose of using consumer sentiment as a near-term predictor of consumer spending (Curtin, 2007, and Greenspan, 2002). Consumer sentiment is not helpful for long-term forecasting. Even though income and consumer spending form a long-run equilibrium relationship, with consumer spending a relatively constant proportion of income, in the short-run their growth rates diverge so that consumers can maximize their lifetime utility for smoothing out consumption. In the long-run, the divergence will reverse itself. It is the strength of consumer sentiment that is important for the analysis of business cycle because it indicates the direction, the timing, and the extent of the divergence (Curtin, 2007).

These results could mean that the information captured by the consumer sentiment data is already captured by the other economic and financial variables. Thus, it appears that consumer sentiment does not provide additional information to predict consumer spending in the near-term.

**TABLE 8: Results of Estimated Short-Run Coefficients using the ARDL Approach**  
**ARDL (4, 1, 0, 3, 2) selected Based on Schwarz Bayesian Criterion**

Variables	Coefficient	Standard Error	T-statistics	P value
dLCSI	.021591	.028931	.74629	[.459]
dLRDI	.16368	.059793	2.7375	[.008]**
dLKLC	.10823	.032387	3.3417	[.002]**
dLTBL	.013189	.025344	.52038	[.605]

\*\* denotes significance at the 5% level

Table 8 depicts the long-run relationship between real consumer spending and the other variables. Here, real disposable income, real stock index and short-term interest rate are statistically and more economically significant in determining consumer spending in the long run. Real stock index is the most economically significant, with a coefficient of 0.866, followed by real disposable income with a coefficient of 0.50 and the short-term interest rate, which has a negative relationship with real consumer spending (coefficient of -0.254).

Again, consumer sentiment is not significant even at the 10% significance level. As consumer sentiment is not meant to be helpful as predictor of consumer spending over a long horizon, these results do not contradict expectation.

TABLE 9: Results of Estimated Long-Run Coefficients using the ARDL Approach

ARDL (4, 1, 0, 3, 2) selected Based on Schwarz Bayesian Criterion

Variables	Coefficient	Standard Error	T-statistics	P value
LCSI	-.13976	.085177	-1.6408	[.107]
LRDI	.50099	.13046	3.8403	[.000]**
LKLC	.86614	.13989	6.1916	[.000]**
LTBL	-.25423	.064096	-3.9664	[.000]**

### 5.7.Variance Decompositions (VDC)

I decided to employ the forecast error variance decompositions (VDC) in order to determine the relative degree of exogeneity and endogeneity of the variables in the model based on a different approach. This is not a regular step following an ARDL model but its results will be a means of comparison of the ranking of the variables with that found with the ARDL methodology. There is no concern with respect to the VAR order level being different to the one obtained for ARDL. For both methodology, the VAR order level is 4.

The VDC measures the contribution of each type of shock to the forecast error variance. It indicates the amount of information each variable contributes to the other variables in the autoregression. The variable that is explained mostly by its own shocks is the most exogenous.

Orthogonalized VDC is not employed due to its limitations. The first limitation is that orthogonalized VDC depends on the ordering of the variables in the VAR and that it is biased towards the first variable in the order. The second limitation is that all other variables are switched off when a particular variable is shocked.

The following tables depict results of the generalized VDC. The results contradict the ARDL findings. According to the generalized VDC, at the end of each forecast horizon (10, 20, 30, 40, 50, 60 and 70 quarters), the most endogenous variable is real disposable income. In the ARDL methodology, real disposable income was found to be the most exogenous variable, on which any change in all other variables depend. Consumer sentiment, on the other hand, is the most exogenous variable at the end of each horizon. This would mean that consumer sentiment has a predictive value on all other variables in the system. In contrast, the ARDL results indicate that consumer sentiment is statistically insignificant in both the short-run and in the long-run. Changes in consumer spending can be explained only by real disposable income at the end of horizon 10 (2.5 years), but can be explained by real stock index and real disposable income at longer horizons which confirms the ARDL findings for the long-term relationship.

TABLE 10: Generalized Variance Decompositions

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
10	LRPC	37	14	3	42	4

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
20	LRPC	37	14	3	42	4

10	LCSI	1	73	20	5	2
10	LRDI	6	26	26	38	3
10	LKLC	9	32	16	37	6
10	LTBL	1	14	2	15	67
	RANK	3	1	5	3	2

20	LCSI	1	74	2
20	LRDI	6	29	2
20	LKLC	8	35	1
20	LTBL	0	16	3
	RANK	3	1	5

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
30	LRPC	35	14	2	43	5
30	LCSI	0	74	21	3	2
30	LRDI	6	31	20	39	4
30	LKLC	8	37	18	31	7
30	LTBL	0	16	3	14	66
	RANK	3	1	5	4	2

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
40	LRPC	35	14	2	43	5
40	LCSI	0	74	21	3	2
40	LRDI	6	31	20	39	4
40	LKLC	8	37	18	31	7
40	LTBL	0	16	3	14	66
	RANK	3	1	5	4	2

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
50	LRPC	35	14	1	44	5
50	LCSI	0	74	21	2	2
50	LRDI	6	33	18	39	4
50	LKLC	8	38	18	28	7
50	LTBL	0	17	4	13	66
	RANK	3	1	5	4	2

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
60	LRPC	34	15	1	45	5
60	LCSI	0	74	21	2	2
60	LRDI	6	33	18	39	4
60	LKLC	8	38	18	28	7
60	LTBL	0	17	4	13	66
	RANK	3	1	5	4	2

HORIZON	VARIABLE	LRPC	LCSI	LRDI	LKLC	LTBL
70	LRPC	34	15	1	45	5
70	LCSI	0	75	22	2	2
70	LRDI	6	34	17	39	4
70	LKLC	8	39	18	27	7
70	LTBL	0	17	4	13	66
	RANK	3	1	5	4	2

### 5.8.CUSUM Test

CUSUM test was introduced proposed by Brown et al (1975) for the study of structural change and the original test statistic was constructed based on cumulated sums of recursive residuals Pesaran (1997) suggests that the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests can be applied to the residuals of the estimated error correction models to test parameter constancy. The existence of co-integration does not necessary imply that the estimated coefficients are stable. If the coefficients are unstable the results will be unreliable. These tests are popular today because they draw attention to structural change and breakpoints in the data.

The CUSUM test uses the cumulative sum of recursive residuals based on the first observations and is updated recursively and plotted against break point. The test is more suitable for detecting systematic changes in the regression coefficients.

The CUSUMSQ makes use of the squared recursive residuals and follows the same procedure. However, it is more useful in situations where the departure from the constancy of the regression coefficients is haphazard and sudden. If the plot of the CUSUM and CUSUMSQ stays within the 5 percent critical bounds, the null hypothesis that all coefficients are stable cannot be rejected. If however, either of the parallel lines are crossed then the null hypothesis of parameter stability is rejected at the 5 percent significance level.

The plots of the CUSUM and CUSUM statistics below are confined within the 5 percent critical value bounds, indicating that the coefficients are stable, and that there is no impact of crisis in the data sample.

Chart 3

Plot of Cumulative Sum of Squares of Recursive Residuals



Chart 4

Plot of Cumulative Sum of Recursive Residuals

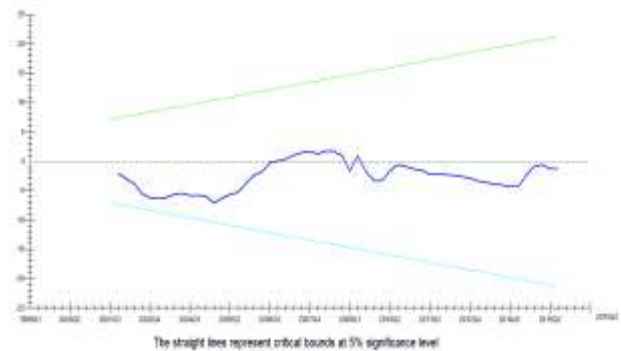


TABLE 11: Diagnostic Tests

Test Statistics	LM TEST	P value
A. Serial correlation	9.3516	[.053]
B. Normality	.092438	[.955]
C. Heteroscedasticity	1.1915	[.275]

Diagnostic tests reveals that the estimation does not have the problem of auto correlation and heteroscedasticity at the 5 percent significance level. Furthermore, the errors in the estimation are normally distributed. To conclude, it can be said that the estimated model which is used for this study is correctly specified, unbiased and consistent. The result boost the confidence of the statistical results which were revealed in the study.

## 6. Conclusion

Consumer spending forms a large component of a nation's gross domestic product (GDP) and it rests upon the behaviour of consumers. Consumer sentiment has been linked to consumer spending in various studies but results have been mixed. This paper contributes to existing literature from the perspective of the Malaysian economy and employs the autoregressive distributed lag (ARDL) approach by Pesaran, Shin, & Smith (2001) to investigate the relationship between consumer sentiment, using the Consumer Sentiment Index (CSI) published by the Malaysian Institute of Economic Research (MIER), and real consumer spending. The ARDL approach overcomes the limitations of conventional cointegration tests, especially their requirement of employing I(1) variables.

It is also of particular interest of this paper to test this relationship alongside other macroeconomic and financial indicators as they may contain much of the same information provided by consumer sentiment. The predictive value of consumer sentiment for near-term forecasting of consumer spending rests upon its ability to provide additional information that is not contained in other economic and financial variables.

This paper finds that (i) a long-term equilibrium relationship exists between real consumer spending, consumer sentiment, real disposable income, short-term interest rate, real stock index when the dependent variable is the short-term interest rate (ii) real disposable income, real stock index and short-term interest rate are statistically and more economically significant in determining consumer spending in the long run than in the short-run (iii) the ECM-ARDL results indicate that real consumer spending, consumer sentiment, real stock index and the three-month interest rate are all dependent on real disposable income (iv) consumer sentiment does not predict real consumer spending in the short-run or in the long-run.

These results could mean that the information captured by the consumer sentiment data is already captured by the other economic and financial variables. Thus, it appears that the CSI does not provide additional information to predict consumer spending in the near-term.

I caution that my results do not prove that consumer sentiment does not predict consumer spending. One of the shortcomings of this approach is that consumer spending was not disaggregated by its major components described in Table 1 and household data was not

disaggregated into demographic and economic subgroups. The approach to using these data as employed in this paper is the more commonly employed approach by many authors but such an approach misses the point made by Curtin (2007) that no single index of consumer sentiment can be devised to accurately predict all types of consumer expenditures at all times. Disaggregation of consumer spending and household data would provide more accurate forecasts. In fact, in his worldwide review and assessment of consumer sentiment surveys, Curtin found that the Malaysian CSI predicts 60 percent of “objectives” which he defined as unemployment rate, consumer price index, short-term interest rate, personal income, gross domestic product, total personal consumption, retail sales, expenditures for durables and vehicle registrations.

Taking cue from the report on consumer sentiment and household expenditure by the New York Federal Reserve (Ludvigson, 2004), investigating the type of questions that generate any predictive value on consumer spending is worthwhile. In the U.S., forecasting consumption appears to be related to the types of questions that make up the survey.

In future, we also need to investigate what causes the movements in the CSI itself. Ludvigson, (2004) has suggested that there may be more complex, possibly non-linear, relationship that exists between consumer sentiment and economic variables, whereas Berry & Davey (2004) have suggested that there are ‘unexplained’ movements in consumer sentiment that are not related to consumer spending. As far as the ARDL results are concerned, it is a starting point for future research to investigate the value of the CSI in predicting macroeconomic variables or otherwise, vice-versa.

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