The Granger Causality between Confidence and Consumption in South Africa

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Vimal Singh

Supervisor: Dr. H. Hove

School of Statistics and Actual Science

A research report submitted to the Faculty of Science,
University of the Witwatersrand, Johannesburg,
in partial fulfilment of the requirements
for the degree of Master of Science.

Johannesburg April 2018

DECLARATION

I declare that this Research Report is my own unaided work. It is being submitted to the degree of Master of Science to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.

……………………………………………………………………….
(Signature of candidate)

Signed on the 11th day of May year 2018 at Johannesburg.

Abstract

South Africa's news headlines are dominated by controversial stories of corruption, crime and politics. This research report investigates if people always accept these events as a "normal" part of the country's history, or if these factors influence or are influenced by expenditure decisions of businesses and consumers. The variables included in the investigation are household consumption, business capital formation, consumer confidence and business confidence. The investigation establishes that these variables are non-stationary and cointegrated, with the cointegrating relationship assessed using Johansen's procedure. The short-run and long run dynamics between the variables are determined using vector error correction models. Granger causality tests were used to explore the causal relationship between the variables.

The Granger Causal relationship between confidence and consumption is assessed using quarterly data from June 1982 to March 2017. It showed that changes in household consumption Granger cause changes in consumer consumption, and no such relationship exists between business confidence and capital formation. The Granger Causal relationship between confidence indicators was also explored, which found that a bi-directional Granger causality relationship existed between business confidence and consumer confidence.

The results of variance decomposition (VDC) and impulse response functions (IRFs) were applied thereafter to further examine the causal relationship between the variables. The former determines the amount each variable contributes to each other while latter assess the impact on the dependent variable given a shock to the system. The results supported the outcome of the Granger causality tests. The variance decomposition found in most cases that a shock to the dependent variable can explain more of the forecast error in the dependent variable than a shock to the other predictor variable. This was observed in the short and long run. The impulse response functions found that confidence measures, both for consumers and businesses, may respond in the initial periods to impulses but the increments of the increase reduce after 1 to 2 periods.

To my wife and parents

Acknowledgements

I take this opportunity to register my appreciation to my supervisor Dr. Herbert Hove for the guidance and supervision to complete my research report. I would like to thank my co-workers for their encouragement and consideration. Finally, I am grateful to my wife for her continuous love and encouragement over these challenging few years. This report would not have been possible without them.

Contents

List of Acronyms

Acronym	Term
AO	Additive Outliers
AIC	Akaike Information Criteria
AR	Autoregressive
BER	Bureau of Economic Research
CCI	Consumer Confidence Index
CE(s)	Cointegrating Equation(s)
CPI	Consumer Price Index
CV	Critical Value
DW	Durbin-Watson Statistic
ECB	European Central Bank
GDP	Gross Domestic Product
GFCF / CF	Gross fixed capital formation
HFCE	Household final consumption expenditure
HQ	Hannan-Quinn criterion
IO	Innovation Outliers
IRF	Impulse Response Function
IRFs	Impulse Response Functions
ME	Maximum eigenvalue Test
OLS	Ordinary Least Squares
PACF	Partial autocorrelation function
SARB	South African Reserve Bank
SBC	Schwarz Bayesian Criterion
SE	Standard Error
TT	Trace Test
VAR	Vector Autoregression
VDC	Variance Decomposition
VECM	Vector Error Correction Model

List of Figures

List of Tables

Chapter 1: Introduction

1.1 Background

The 2017 first quarter Gross Domestic Product (*GDP*) growth figures that Statistics South Africa released, revealed that the country's economy contracted 0.7% during the period. This preceded by a contraction of 0.3% reported in the last quarter of 2016. Consecutive contractions in growth over two quarters is an indication of the country entering a technical recession. Events such as electricity outages, strike activity in the platinum and motor sectors, the state capture report released by the Public Protector, the Cabinet reshuffle and the credit ratings downgrade have led to a lack in confidence by households and businesses over the years. This lack in confidence translated into delayed purchase decisions by both households and businesses which ultimately put the economy into recession. More stable economic environments help improve confidence levels (*Fin24, 2017*).

Over the last 5 years, South Africa's GDP growth rate was on average half that of neighbouring countries. This has led to South Africa being in danger of sliding backwards towards third world status from a promising market-leading position in Southern Africa (*Yeo, 2017*). GDP growth is at risk of approaching the 1% year-on-year mark in 2017 after recording 2.5% and 3.6% for 2012 and 2011 respectively (*Mabena, 2017*). The South African Reserve Bank (*SARB*) also noted, in the final 2016 Quarterly Bulletin, that subdued business and consumer confidence levels that suppressed fixed investment was among the influential attributes which resulted in the lacklustre performance of the South African economy in 2016 (*South African Reserve Bank, 2017*).

The focus of this research report is to determine if associations exist between confidence and consumption components of the GDP using South African economic data from June 1982 to March 2017. This research report will investigate if people always accept the above events as a "normal" part of the country's history, or if these factors influence or are influenced by consumption behaviour.

The time series data, which will be used in this research report, are subject to local trends, highs and lows (cyclical variation) which may not be regular. Methods for analysing a single time series were developed by Box and Jenkins (*1970*). Following the work of Granger and his co-authors, the joint analysis of a pair or more of such series is now well established (*Granger and Ghysels, 2001*). Often, the linear combination of a pair of integrated series may be stationary and this property is known as cointegration. The cointegration property can be explained by considering a drunk walking his dog (*Murray, 1994*). Though the drunk and the dog each follow a random path, they stay close to each other. Thus, the distance between the random paths would likely give a stationary series. That is, any pair of integrated series are cointegrated provided a linear combination between them is stationary.

If confidence and consumption are cointegrated, then they share a stationary equilibrium relation. In this context, cointegration resembles the presence of a long run equilibrium to which the system converges. If there is a deviation from this long run equilibrium, then it will only be temporary since the linear combination between them will ultimately return to its equilibrium. Consequently, the relationship between a pair of cointegrated series is that of error correction and can therefore be modelled by a vector error correction model ($VECM$) (*Engle and Granger, 1987*). It follows from the idea of cointegration that given a pair of cointegrated series, at least one of them must cause the other. This leads to the concept of causality.

There is however no widely accepted definition of “true causality”. All refer to the relationship between events, processes or entities such that when one occurs, the other follows. That is, one has the tendency to produce or alter another and without one, the other could not occur. Granger (*1969*) defined causality as a statistical concept that is focussed on prediction. That is, a time series X_t causes Y_t if past values of X_t contain information that is useful when predicting Y_t in addition to the information that previous values of Y_t contain. It is this definition of causality (*Granger causality henceforth*) which will be adopted in this research report.

1.2 Aim and Objectives of the research report

The aim of this research report is to determine the appropriate causal relations between confidence and consumption using South African data. The specific objectives are as follows:

1. Determine if a causal relationship exists between:
    a. consumer confidence and consumer consumption,
    b. business confidence and business consumption and
    c. consumer confidence and business confidence.
2. Determine the direction of the causal relationship based on the above outcomes.
3. Determine the amount of information each variable contributes to the other variables in the defined model using variance decomposition (VDC).
4. Describe how consumption reacts over time to shocks in confidence using impulse response functions (IRFs).

1.3 Data

Data for this research report has been sourced from EasyData, an online resource host that provides access to South African economic and financial data. The household final consumption expenditure (*HFCE*) is the largest part of the expenditure-based gross domestic product (*GDP(E)*) and represents consumption of consumers. Gross fixed capital formation (CF *henceforth*) by private enterprises is a part of GDP that categorises transactions on the net acquisitions of new as well as existing capital assets. CF is an indication of consumption behaviour of businesses to keep operating (*Statistics South Africa, 2016*). The consumption and confidence data are publicly available from SARB and the Bureau of Economic Research (*BER*) websites respectively and are made available by EasyData too. The quarterly FNB/BER Consumer Confidence Index (*CCI*) will be the measure of confidence representing households in this research report. Similarly, the quarterly Business Confidence Index (*BCI*), also published by BER, will be used as the measure of confidence for businesses. A more comprehensive description of the variables is provided in Appendix A.

1.4 Organisation of the Research Report

The rest of the research report is organised as follows. Time series models which will be considered when analysing Granger causality are set out in Chapter 2. Chapter 3 gives a review of the related literature. The implementation of the possible methodologies is the subject of Chapter 4 and the results of the study are presented and discussed in Chapter 5. Detailed results of the stability tests and lag length selection are provided in the appendix. Chapter 6 concludes the work.

Chapter 2: Background Theory

2.1 Time Series Models

Consumption and confidence, the time series of interest in this research report, are evaluated on a quarterly basis. An autoregressive ($AR(p)$) model is a time series regression model in which the regressors are the past values $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$ of the dependent variable Y_t. The general $AR(p)$ model has the form:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + \varepsilon_t \ , \quad (1)$$

where $t \in \mathbb{Z}^+, p$ is the order of the model determined using F test, t test, Akaike information criteria (AIC) or Schwarz Bayesian Criterion (SBC); and ε_t represents the error term which is assumed to have a normal distribution with mean zero and a constant variance. The autocovariance and autocorrelation are measures of dependence between observations in a time series. Autocorrelation or serial correlation is defined as the correlation of a series with its own lagged values. A plot of the autocorrelation function (ACF) against time t is called a correlogram. The ACF can be used to identify the possible structure of time series data. The partial correlation is a correlation between two lagged values of a time series while controlling for the effects of the intervening lagging values. A plot of the partial autocorrelation function ($PACF$) against time t is called the partial correlogram. The ACF not decreasing to zero or decaying slowly suggests non-stationarity (Box and Jenkins, *1970*).

A Vector Autoregression (VAR) is a generalisation of the univariate $AR(p)$ model by allowing for more than one evolving variable. It is best explained by starting with an expansion of the $AR(p)$. The expansion entails adding more variables to improve the prediction of Y_t model yielding an autoregressive distributed lag (ADL) model. An ADL model with p lags of Y and q lags of X, as determined by the ACF and $PACF$, has the form:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + \delta_1 X_{t-1} + \cdots + \delta_q X_{t-q} + \varepsilon_t \quad (2)$$

where $t \in \mathbb{Z}^+, p \in \mathbb{Z}^+, q \in \mathbb{Z}^+$ and is denoted by $ADL(p, q)$.

A bivariate VAR model for $t = 1,2, \ldots, n$ has the form:

$$Y_t = \alpha_1 + \beta_{11} Y_{t-1} + \cdots + \beta_{1p} Y_{t-p} + \delta_{11} X_{t-1} + \cdots + \delta_{1q} X_{t-q} + \varepsilon_{1t}$$
$$X_t = \alpha_2 + \beta_{21} Y_{t-1} + \cdots + \beta_{2p} Y_{t-p} + \delta_{21} X_{t-1} + \cdots + \delta_{2q} X_{t-q} + \varepsilon_{2t} \quad (3)$$

In general, p-variable VAR has p equations for each dependent variable, and each equation uses as its explanatory variables, some lags of all the variables under study. The coefficients of a VAR are estimated by estimating each equation using ordinary least squares (*OLS*) while the optimal lag lengths p and q are selected using information criteria (*Stock and Watson, 2006*).

There is a decrease in forecast accuracy if too few lags are used and an increase in estimation uncertainty by adding too many lags. The choice of lags must balance the benefit of using additional information against the cost of estimating the additional coefficients. Akaike information criteria (AIC) and Schwarz Bayesian Criterion (SBC) information criteria are generally used when selecting the optimal lag length p. They are expressed as

$$AIC(p+q) = \ln\left(\frac{SSR(p+q)}{n}\right) + (p+q+1)\frac{2}{V}$$

$$SBC(p+q) = \ln\left(\frac{SSR(p+q)}{n}\right) + (p+q+1)\frac{\ln(V)}{V} \quad (4)$$

where $SSR(p+q)$ is the sum of squared residuals of the estimated $AR(p+q)$, $p = 1, \dots, n$, $q = 1, \dots, n$ and V is the total parameters being considered. The $(p+q)$ which minimises the information criteria among the possible choices is selected. The variance of the forecast error due to estimation error increases with $(p+q)$ and thus a forecasting model with too many coefficients is not preferred. The SBC has a penalty for using more parameters ($In(V)$) and increasing forecast variance. The AIC has a smaller penalty term than BIC (i.e. $2 < \ln(V)$). The AIC will therefore estimate more lags than the BIC which may result in an overestimate of $(p+q)$. The AIC may therefore only be desirable when longer lags may be important to consider for the model (*Stock and Watson, 2006*).

2.2 Stationarity

In time series analysis, there is only one finite realisation (or sample path), called a time series from the data generating process. Thus, unless one assumes time homogeneity of the data generating process, there will be no basis for inference and prediction from a time series variable. Time series analysis uses stationarity as its form of time homogeneity. It is defined as time invariance of the entire probability distribution of the data generating process (strict stationarity), or that of the first and second moment (known as weak-sense stationary, covariance stationary or second-order stationary).

The process $\{Y_t\}$ is strictly stationary if for all $k \in \mathbb{N}$, $h \in \mathbb{Z}^+$, and $(t_1, t_2, \dots, t_k) \in \mathbb{Z}^k$, $(Y_{t_1}, \dots, Y_{t_k}) \stackrel{d}{=} (Y_{t_1+h}, \dots, Y_{t_k+h})$ where $\stackrel{d}{=}$ denotes equality in distribution and h a point in time in the future. It is weakly (or covariance) stationary if for all $h, t \in \mathbb{Z}^+$, $E(Y_t) = \mu$, a constant and

$Cov(Y_t, Y_{t+k}) = \gamma_k$ with $\sigma_Y^2 = \gamma_0 < \infty$. Unless stated otherwise, the term stationary will be used to mean weak or covariance stationary in this research report.

An important example of a weakly stationary process is the white noise process. A stochastic process $\{\varepsilon_t, t \in \mathbb{Z}\}$ is defined as zero mean white noise (*Triacca, 2014)* if

- $E(\varepsilon_t) = 0 \; \forall \; t$
- $Var(\varepsilon_t) = \sigma_\varepsilon^2 < \infty \; \forall \; t$ and
- $Cov(\varepsilon_t, \varepsilon_\tau) = 0$ for $t \neq \tau$.

White noise processes usually arise as residual series when fitting time series models (*Dettling, 2013*).

2.3 Trends and Unit Root Tests

Several observed economic and financial time series data reveal trends in their behaviour or non-stationarity in the mean. Two popular models for non-stationary time series with a trending mean are trend stationarity and difference stationary processes. For such series, some form of trend removal is required. In the former case the underlying trend can be removed (detrended) leaving a stationary process, i.e. the series does not possess unit roots while in the latter differencing is required once or more for a process possessing unit roots.

2.3.1 Trend Stationarity

A series which fluctuates around a deterministic trend is called trend stationary. The simplest form of a trend stationary model for the time series process $\{Y_t\}$ is

$$Y_t = \gamma + \beta t + \varepsilon_t \tag{5}$$

where, γ is a constant, $\beta \neq 0$ and ε_t is white noise. The mean of the series (deterministic trend), $E(Y_t) = \gamma + \beta t$ is time dependent and accounts for sustained increase (or decrease) in the series over time. For example, consumption is expected to have an upward trend on average due to the yearly inflationary increase in the cost of goods and services. Because of the time varying mean, the series cannot be stationary. Consequently, if the variation in the mean can be adequately explained by some form of deterministic trend term estimated from the data, then the detrended series $Y_t^* = \varepsilon_t$ where $Y_t^* = Y_t - \gamma - \beta t$ will be stationary.

2.3.2 Difference Stationary Series

A series can be made stationary by differencing an appropriate number of times. Such a series is called a difference stationary series. For a series $\{Y_t\}$, consider the model

$$Y_t = \gamma + \varphi_1 Y_{t-1} + \beta t + \varepsilon_t \, . \qquad (6)$$

The model in equation (2) has several special cases. When $\gamma \neq 0, \varphi_1 = 1, \beta \neq 0$, Y_t is both a trend and difference stationary series. When $\gamma = 0, \varphi_1 = 1, \beta = 0$, Y_t is a random walk which is represented as $Y_t = Y_{t-1} + \varepsilon_t$. Observe that $Y_t - Y_{t-1} = \Delta Y_t = \varepsilon_t$ is stationary. That is, $\{Y_t\}$ is a differenced stationary process. It is called integrated of first order, $I(1)$ process (possesses a unit root) since it becomes stationary after being differenced once. Starting the process at $t = 0$ with a fixed initial value Y_0 results in $Y_t = Y_0 + \sum_{i=1}^{t} \varepsilon_i$ with moments $E(Y_t) = Y_0$ and $Var(Y_t) = t.\sigma^2$, and therefore cannot be stationary. In addition, the shocks will have permanent effects. When $\gamma \neq 0, \varphi_1 = 1, \beta = 0$, Y_t is a random walk with drift.

2.3.3 Stationarity Tests

The presence of unit roots in time series variables results in standard distribution theory not being valid as the shape of the distribution changes over time. Testing for stationarity of the time series variables before any analysis is therefore necessary.

a) Dickey-Fuller (DF) test

This test considers an $AR(1)$ model $Y_t = \rho Y_{t-1} + \varepsilon_t$ where ε_t is white noise. If $\rho = 1$, Y_t is defined as a simple random walk which is non-stationary. The null hypothesis when testing if a series has non-stationary properties is $H_0\colon \rho = 1$. It is tested against the alternative hypothesis $H_1\colon \rho < 1$. $|\rho| > 1$ is not considered since this is an explosive process and, would unlikely occur for economic and financial data (*Boero, 2009*).

Alternatively, the $AR(1)$ model can be specified as

$$\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t \text{ where } \gamma = \rho - 1 \qquad (7)$$

The null hypothesis $H_0\colon \rho = 1$ becomes equivalent to $H_0\colon \gamma = 0$ (the series has a unit root), and the alternative hypothesis is $H_1\colon \gamma < 0$ (a stationary series).

An $AR(1)$ model may contain a constant term α yielding

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \varepsilon_t \qquad (8)$$

or a constant term α and a trend term βt to give

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \varepsilon_t \, . \qquad (9)$$

OLS is used to estimate equations 3, 4 and 5. The t-statistic of the coefficient γ is assessed against the appropriate critical values to determine its significance. If H_0 is rejected, then for $AR(1)$, Y_t is stationary with zero mean. For $AR(1)$ with a constant term α, Y_t is stationary with a non-zero mean whereas for $AR(1)$ with a constant term α and trend term βt, Y_t is stationary around the mean of the series $\alpha + \beta t$.

b) The Augmented Dickey-Fuller (ADF) Test

The Dickey-Fuller statistic applies only to an $AR(1)$ model. For some series, this model does not capture all the serial correlation in Y_t in which case a higher-order autoregression is more appropriate. An extension of the Dickey-Fuller test to the $AR(p)$ model is the Augmented Dickey-Fuller (ADF) test. The ADF test is used to test if the errors ε_t for an $AR(p)$ model are serially correlated. The null hypothesis $H_0: \gamma = 0$ (Y_t has a stochastic trend) is tested against the alternative hypothesis $H_1: \gamma < 0$ (Y_t is stationary) in the regression

$$\Delta Y_t = \beta_0 + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_p \Delta Y_{t-p} + \varepsilon_t \tag{10}$$

If Y_t is stationary around a deterministic linear time trend, then this trend $\beta_0 + \alpha t$ must be added, in which case the regression model becomes

$$\Delta Y_t = \beta_0 + \alpha t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_p \Delta Y_{t-p} + \varepsilon_t \tag{11}$$

where, α is an unknown coefficient and the ADF statistic is the OLS t-statistic testing $\gamma = 0$ (*Stock and Watson, 2006*).

c) Phillips and Perron test

The Phillips and Perron (PP) test also tests the null hypothesis $\gamma = 0$ (unit root) but with no lagged difference terms ΔY_{t-j}. The $AR(p)$ model is instead estimated by OLS (with the optional inclusion of the deterministic variables) and the Newey-West procedure (a nonparametric method) is used to address the serial correlation in ε_t for the t-statistic of the coefficient. This test can be more effective than the ADF test and it will not produce biased results with extra lags (*Boero, 2009*).

The PP test can be used as an alternative or with the ADF tests based on the diagnostic statistics from the DF and ADF tests. The PP test does not require a decision to be made regarding lags *(Boero, 2009).*

d) Units Roots with Break Points

ADF and PP unit root tests may not be successful to reject the unit root null hypothesis when the series has structural breaks. Breaks need to be recognised and accounted for in the model otherwise the OLS estimates will determine a relationship that holds on average leading to poor forecasts (*Stock and Watson, 2006*). Applying unit root tests which allow for the possible presence of structural breaks avoids test results which may be biased towards non-rejection of the null hypothesis (*Perron, 1989*).

Splitting the time series into segments and running the ADF tests on each of them is a simple approach to test for stationarity in the presence of structural breaks. The problem with this approach is that prior knowledge about the location of the breaks is required. The Perron-Vogelsang and Clemente-Montanes-Reyes unit root tests are suitable when the break date(s) are unknown. These procedures detect the dates of structural breaks, and assist with identifying variables associated with events such as changes in fiscal policy, monetary policy, political turmoil, etc. The null hypothesis of a unit root with breaks is tested against the alternative that the series is stationary with breaks. The ADF and PP tests can rather be used if these tests do not detect structural breaks (*Feridun, 2009*). These tests use modified Dickey-Fuller (DF) unit root tests with the inclusion of dummy variables to account for structural breaks.

The Perron-Vogelsang and Clemente-Montanes-Reyes unit root test models have two forms. The first form caters for a steady change in the series mean and is called the Innovation Outliers (IO) model. The second form captures sudden change (crash) in the series mean and is called the Additive Outliers (AO) model (*Feridun, 2009*). Perron (1994) discusses two Innovation Outliers (IO) models. The first handles for steady change in the intercept only and has the form:

$$Y_t = \beta_0 + \theta DU_t + \alpha t + \varrho D(T_b)_t + \gamma Y_{t-1} + \delta_1 Y_{t-1} + \cdots + \delta_p Y_{t-p} + \varepsilon_t. \quad (12)$$

The second handles for steady change in the intercept and the slope of the trend function, and has the form:

$$Y_t = \beta_0 + \theta DU_t + \alpha t + \psi DT_t + \varrho D(T_b)_t + \gamma Y_{t-1} + \delta_1 Y_{t-1} + \cdots + \delta_p Y_{t-p} + \varepsilon_t \quad (13)$$

where T_b is the break date which is unknown and is determined using data within the model, DU_t is the dummy variable for the intercept ($DU_t = 1$ if $t > T_b$ and zero otherwise), DT_t is the dummy variable for slope ($DT_t = T_t$ if $t > T_b$ and zero otherwise), and $D(T_b)_t$ is the dummy variable for the crash ($D(T_b)_t = 1$ if $t = T_b + 1$ and zero otherwise). The break date can be estimated by minimising the value of the t-statistic for testing $\alpha = 1$. It can also be estimated by maximising or minimising the absolute value of the t-statistic on the break parameters associated with either the intercept or slope (*Harvin and Pahlavani, 2006*).

A two-step procedure is used to test for a unit root in an AO model. The series is first detrended by regressing it on the trend components (including constant, time-trend and dummy break):

$$Y_t = \beta_0 + \alpha t + \sum_{i=1}^{k} c_i \Delta\, Y_{t-i} + \varepsilon_t \text{ where } k = 1, \ldots, n \quad (14)$$

Like the IO methodology, these equations are estimated sequentially for all possible values of T_b ($T_b = \mathrm{k}+2, \dots, \mathrm{T}-1$) where T is the total number of observations to minimise the t-statistic for $\alpha = 1$. The detrended series is used to test for a unit root using a modified Dickey-Fuller regression in the second step. The null hypothesis is rejected if the t-statistic is larger in absolute value than the corresponding critical value (*Harvin and Pahlavani, 2006*).

2.4 Cointegration

This section describes how cointegrated non-stationary variables can be used to formulate and estimate a model with an error correction mechanism. Finance and Economic theory often suggests the existence of long run equilibrium relationships among non-stationary time series variables. If these variables are integrated of order d ($I(d)$), then cointegration techniques can be used to model these long run relations. Two series X_t and Y_t, are said to be cointegrated of order d, b where $d \geq b \geq 0$, written as $(X_t, Y_t) \sim CI(d, b)$, if:

(i) both series are $I(d)$ and,
(ii) there exists a vector (α_1, α_2) such that $\alpha_1 X_t + \alpha_2 Y_t$ is integrated of order $d - b$. Engle and Granger *(1987*) referred to (α_1, α_2) as the cointegrating vector.

Therefore, unless the series are cointegrated, any random linear combination of $I(d)$ series will continue to be $I(d)$. If a valid error correction representation of X_t and Y_t exists, then these variables are cointegrated and vice versa. That is, there must be some force or adjustment process which pulls the equilibrium error back to zero and, so that X_t and Y_t have a long run relationship. This errors in the long run relationship is prevented from becoming increasingly larger by the adjustment process. Identifying cointegrated series allows for the improvement of long run forecast accuracy (*Boero, 2009*).

Approaches to determine the cointegration between variables and estimate the long run relationship exist in the literature. These include the Engle and Granger approach, Johansen's procedure and Phillips–Ouliaris cointegration method. The approaches determine the cointegration between variables, estimate the long run relationship, and thereafter specify an error correction model representing the short-run adjustment towards equilibrium (*Koekemoer, 1999*). The Phillips–Ouliaris method does have a similar shortcoming to the Engle and Granger approach in that it can only estimate single cointegrating relationships. On the other hand, the Johansen's procedure has the remedy to the limitation of the Engle and Granger approach and Phillips–Ouliaris method (*Ssekuma, 2011*). The Engle and Granger approach (a single equation cointegration technique) and Johansen's procedure (a multivariate cointegration technique) will therefore be discussed next.

2.4.1 The Engle and Granger Cointegration approach

Engle and Granger (1987) proposed a two-step procedure for cointegration analysis as follows:

Step 1: Estimate the long run equilibrium equation

Consider the long run relation for the bivariate case

$$Y_t = \varphi X_t + \varepsilon_t \,, \tag{15}$$

where X_t and Y_t are $I(1)$, and φ is an unknown coefficient. This first step entails estimating equation (15) using OLS and thereafter testing the stationarity of the residuals $\hat{\varepsilon}_t = Y_t - \hat{\varphi} X_t$. The null and alternative hypothesis are therefore

$$H_0: \hat{\varepsilon}_t \sim I(1) \text{ versus } H_1: \hat{\varepsilon}_t \sim I(0)$$

If the null hypothesis is rejected it implies that the 2 series are cointegrated (*Koekemoer, 1999*).

Step 2: Estimation of the Error Correction Model

Continuing from step one, if X_t and Y_t are $I(1)$ and for some coefficient φ, $Y_t - \varphi X_t$ is $I(0)$, then X_t and Y_t are said to be cointegrated. The coefficient φ is the integration coefficient. Equation (15) can be estimated replacing φ with the OLS estimated $\hat{\varphi}$

$$\Delta Y_t = \beta_1 \Delta Y_{t-1} + \gamma_1 \Delta X_t + \alpha(Y_{t-1} - \hat{\varphi} X_{t-1}) + \varepsilon_t \,, \tag{16}$$

where ε_t is the error term and α is negative to ensure convergence of the model in the long run. ΔY_t, ΔX_t and $(Y_{t-1} - \hat{\varphi} X_{t-1})$ are all $I(0)$, and provided the model is properly specified, ε_t is also $I(0)$. The term $Y_{t-1} - \hat{\varphi} X_{t-1}$ is the error correction term. Equation (16) represents the error correction model which describes how X_t and Y_t behave in the short run consistent with a long run cointegrating relationship. The $VECM$ is estimated using OLS as these equations have only $I(0)$ variables. The speed of adjustment towards equilibrium is indicated by the slope coefficient α in equation (16) (*Koekemoer, 1999*).

In models where there is a unique cointegrating vector, the relative simplicity of Engle-Granger approach is an advantage. It also allows for the use of the super consistency property of OLS to obtain estimates of the coefficients of the cointegrating vector which are close to the true value of the coefficients (*Koekemoer, 1999*). However, with more than two series, there may be multiple cointegration vectors and this approach cannot determine how many exist. A further restriction is that the estimation of the long run equilibrium regression requires a variable assigned as the response variable and the other variable as the predictor variable. It also operates on the principle that irrespective of which variable is chosen for normalisation, the same results will be attained if variables are interchanged which does not generally hold in practice (*Ssekuma, 2011*).

2.4.2 Cointegration: the Johansen's procedure

An alternative approach to test for cointegration was introduced by Johansen (1988). This procedure avoids the fundamental problem discussed in the Engle-Granger approach of being unable to apply restrictions to the cointegrating vectors. It tests the number of cointegrating relations directly. The Johansen test is a multivariate generalisation of the ADF test. The generalisation is the examination of linear combinations of variables for unit roots. All variables are treated the same and none of them are influenced by factors internal or external to the model. The Johansen procedure has two steps. The first step is to determine the number of cointegrating vectors and the second step is to estimate the number of cointegrating relationships.

Step 1: Determination of the number of Cointegrating Vectors

Begin by considering the data generating process of a vector $\boldsymbol{Y}_t$ of n potential endogenous variables, as an unrestricted $VAR(p)$ model involving up to p lags of $\boldsymbol{Y}_t$:

$$\boldsymbol{Y}_t = \mathbf{A}_1\boldsymbol{Y}_{t-1} + \ldots + \mathbf{A}_p\boldsymbol{Y}_{t-p} + \boldsymbol{\varepsilon}_t \, , \tag{17}$$

where, $\boldsymbol{Y_t}$ is $(p\times1)$ vector, each of the $\mathbf{A}_i$ is a $(p\times p)$ matrix of parameters for $i = 1,2,\ldots,p$ and $\boldsymbol{\varepsilon}_t$ is a $(p\times1)$ vector. Subtracting $\boldsymbol{Y}_{t-1}$ from both sides of the system (17) of equations and, adding and subtracting $\boldsymbol{Y}_{t-p+1}$ on the right-hand side yields:

$$\Delta\boldsymbol{Y}_t = \boldsymbol{\Gamma}_1\Delta\boldsymbol{Y}_{t-1} + \ldots + \boldsymbol{\Gamma}_{p-1}\Delta\boldsymbol{Y}_{t-p+1} + \boldsymbol{\Pi}\boldsymbol{Y}_{t-p} + \boldsymbol{\varepsilon}_t \, , \tag{18}$$

where $\boldsymbol{\Pi} = -(\boldsymbol{I}_p - \mathbf{A}_1 - \cdots - \mathbf{A}_i)$, $\boldsymbol{I}_p$ is an identity matrix, $\boldsymbol{\Gamma}_k = -(\boldsymbol{I}_p - \mathbf{A}_1 - \cdots - \mathbf{A}_k)$ and $k = 1,\ldots,p-1$. Expressed in this way system (18) contains information on both the short and long run adjustment to changes in $\boldsymbol{Y}_t$ by means of the estimates of $\hat{\boldsymbol{\Pi}}$ and $\hat{\boldsymbol{\Gamma}}_k$. In particular, it can be shown that $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ represents the speed of the adjustment to equilibrium and $\boldsymbol{\beta}$ represents the matrix of long run coefficients. In the multivariate model, $\boldsymbol{\beta}'\boldsymbol{Y_t}$ represents up to $(n-1)$ cointegration relationships, which ensures that $\boldsymbol{Y_t}$ converges to equilibrium. Assuming, that $\boldsymbol{Y_t}$ is a vector of non-stationary $I(1)$ variables, then all the terms in (18) which involve $\boldsymbol{Y_{t-1}}$ are $I(0)$, while $\boldsymbol{\Pi}\boldsymbol{Y_{t-1}}$ must also be stationary for $\boldsymbol{\varepsilon}_t \sim I(0)$ to be white noise. Stationarity of $\boldsymbol{\Pi}\boldsymbol{Y_{t-1}}$ implies that the long run cointegrating relationships between the variables in levels is inherent. The number of cointegrating relationships present amongst variables in the model, as well as the nature of these relationships can be determined by the Johansen technique (*Koekemoer, 1999*).

The number of linear combinations which exist amongst the variables is determined by the rank of the matrix $\boldsymbol{\Pi}$. $\boldsymbol{\Pi}$ will be an $n\times n$ matrix when the system has n variables with a rank between zero and n. A rank of zero will indicate the variables are $I(1)$ and that they are not cointegrated. A rank of n will indicate that the matrix has full rank and therefore has n independent stationary linear combinations of the variables. Testing to identify the number of cointegrating vectors is equivalent to testing for the eigenvalues greater than zero in the matrix $\mathbf{\Pi}$. Johansen (1988), Johansen and Juselius (1990) calculated the critical values to test the rank of the matrix $\mathbf{\Pi}$. The maximum eigenvalue test and the trace test are used to determine the rank of $\mathbf{\Pi}$.

Consider the arbitrary eigenvalues of the matrix $\mathbf{\Pi}$ ordered as: $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$. If there are r cointegrating vectors, then $\log(1-\lambda_j) = 0$ for the smallest $n-r$ eigenvalues for $j = r+1, r+2, \ldots, n$. The hypothesis of the cointegration test is effectively testing $\lambda_j = 0$ (no cointegrating vectors), against $\lambda_j \neq 0$ (at least one cointegrating vector). The maximum eigenvalue test (ME) as well as the trace test (TT) use the estimated eigenvalues $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \ldots \geq \hat{\lambda}_n$ to test the hypothesis about the rank of $\mathbf{\Pi}$. The tests are run sequentially, beginning from $\hat{\lambda}_1$ to $\hat{\lambda}_n$ *(Boero, 2009).*

The maximum eigenvalue test is used to test whether the estimated $(r+1)^{th}$ largest eigenvalue is significantly different from zero. The null and alternative hypothesis are therefore

$$H_0\text{: rank} \leq r \text{ versus } H_1\text{: rank} = r+1.$$

The test statistic is defined by

$$\lambda_{max} = -N \ln\left(1 - \hat{\lambda}_{r+1}\right), r = 0,1, \ldots, n-1 \quad (19)$$

where N is the number of observations in sample of data and n is the maximum number of possible cointegrating vectors.

The trace test on the other hand tests whether the smallest $n-r$ estimated eigenvalues are significantly different from zero. The null and alternative hypothesis are therefore

$$H_0\text{: rank} \leq r \text{ versus } H_1\text{: rank} \geq r+1.$$

The test statistic is defined by:

$$\lambda_{trace} = -N \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right), r = 0,1, \ldots, n-1\ . \quad (20)$$

The number of cointegrating vectors, r which have been determined will be an input in the next step. The λ_{max} and λ_{trace} statistics are compared to the appropriate critical values which follow a non-standard distribution and is dependent on the deterministic terms (e.g. constants, dummies, trend etc.) in the equations.

Step 2: Estimation of Cointegrating Relationships

The cointegrating relationships is determined in this step. The Reduced rank regression method is used to extract information and requires equation (7) in the form:

$$\Delta \boldsymbol{Y}_t - \boldsymbol{\alpha\beta}'\boldsymbol{Y}_{t-1} = \boldsymbol{\Gamma}_1 \boldsymbol{\Delta Y}_{t-1} + \ldots + \boldsymbol{\Gamma}_{p-1}\boldsymbol{\Delta Y}_{t-p+1} + \boldsymbol{\varepsilon}_t \quad (21)$$

For r cointegrating vectors, $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta}'$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $n \times r$ matrices. The maximum eigen value test and the trace test require the factorisation of $\boldsymbol{\Pi}$ by a calculation method using reduced rank regression and involving canonical correlation. The maximum likelihood estimate of $\boldsymbol{\beta}$ are the eigenvectors corresponding to the r highest eigenvalues.

The Johansen's procedure requires that the residuals $\boldsymbol{\varepsilon}_t$ be independent and identically distributed. Autocorrelation can be eliminated from the VAR by selecting sufficient lags using the information criteria procedures. The main advantage of this procedure over the Engle-Granger methodology is that it can be used to test a few hypotheses about the variables *(Boero, 2009)*. If cointegration has been detected between variables, then there exists a long-term equilibrium relationship between them. Consequently, a $VECM$ can be applied to evaluate the short run properties of the cointegrated series.

The Johansen's procedure assumes that the cointegrating vector remains constant during the period of study. In practice however, long run relationships between the underlying variables change. The reason for this might be technological progress, economic crisis, changes in people's preferences and behaviour, policy or regime alteration and institutional development. This limitation can only be experienced if the sample period under consideration is long (*Ssekuma, 2011*) and the susceptible nature of the variable to change (e.g. computer technology changes frequently and long-time period is greater than 12 months; people's preferences change slower, and a long-time period could be 5 years, etc).

2.5 Granger Causality

If past values of a time series, say $\{X_t\}$, contain extra information that helps explain and predict another time series, say $\{Y_t\}$, then X_t is said to Granger cause Y_t. Otherwise, X_t fails to Granger cause Y_t if $\forall\ s = 1,2, \ldots$

$$MSE[\widehat{\mathrm{E}}(Y_{\mathrm{t+s}}|Y_t, Y_{t-1}, \ldots)] = MSE[\widehat{\mathrm{E}}(Y_{\mathrm{t+s}}|Y_t, Y_{t-1}, \ldots, X_{t-1}, X_{t-2}, \ldots)] \quad (22)$$

where, Ω_t represents all knowledge in the universe at time t and $\hat{E}[Y_{\mathrm{t+s}}|\Omega_t]$ is a linear forecast of $Y_{\mathrm{t+s}}$ based on information at time t.

Granger causality between two variables cannot be interpreted as a real causal relationship but merely shows that one variable can help to predict the other one better. Two assumptions of Granger causality are that the future cannot predict the past and a cause contains unique information not available elsewhere about an effect. If a pair of series is cointegrated, then at least one of them must cause the other.

2.5.1 Test for Granger causality

Consider a bivariate $VECM$ model:

$$\Delta Y_t = \beta_{10} + \beta_{11}\Delta Y_{t-1} + \cdots + \beta_{1p}\Delta Y_{t-p} + \gamma_{11}\Delta X_{t-1} + \cdots + \gamma_{1p}\Delta X_{t-p} + \alpha_1(Y_{t-1} - \theta X_{t-1}) + \varepsilon_{1t} \quad (23)$$

$$\Delta X_t = \beta_{20} + \beta_{21}\Delta Y_{t-1} + \cdots + \beta_{2p}\Delta Y_{t-p} + \gamma_{21}\Delta X_{t-1} + \cdots + \gamma_{2q}\Delta X_{t-q} + \alpha_2(Y_{t-1} - \theta X_{t-1}) + \varepsilon_{2t} \quad (24)$$

- To determine if X_t Granger causes Y_t. That is,

  $$H_0: \gamma_{11} = \ldots = \gamma_{1p} = 0 \text{ versus } H_1: \gamma_{1i} \neq 0 \text{ for any } i$$

- To determine if Y_t Granger causes X_t. That is,

  $$H_0: \beta_{21} = \ldots = \beta_{2p} = 0 \text{ versus } H_1: \beta_{2\mathrm{j}} \neq 0 \text{ for any } j$$

The first step of Granger causality test requires ΔY_t of (23) to be regressed on its past values excluding ΔX_t in the regressors. This is called the restricted regression, from which the restricted sum of squared residuals (SSR_r) is obtained. The second step requires ΔY_t to be computed including the lagged ΔX_t. This is called the unrestricted regression from which the unrestricted sum of squared residuals (SSR_u) is obtained. The test statistic is defined as

$$F = \frac{\frac{(SSR_r - SSR_u)}{n}}{\frac{(SSR_u)}{\Theta - (p + q + 1)}} \quad (25)$$

where Θ is the number of observations and, p and q are the number of lags determined for (23) using AIC or SBC. The test statistic (25) will be compared with $F_{n,\Theta-(p+q+1)}(\alpha)$ to assess the null hypothesis. The same procedure is used to test for the inverse Granger-causality relation in (24) (*Foresti, 2006*).

Granger Causality test without considering the effect of other variables is subject to possible specification bias. A causality test is sensitive to model specification and the number of lags (*Alimi and Ofonyelu, 2013).* A complete understanding of the way the variables of the system interact with each other may also not be known using Granger causality. A system may contain several other variables and there may be interest in understanding how a variable responds to an impulse in another variable. This leads to the next section on impulse response functions.

2.6 Impulse Response Functions (IRFs) and Variance decomposition (VDC)

Impulse response analysis (IRF) is a common tool for investigating the interrelationships among the variables in time series models. In terms of consumption, only the relationship with confidence is being considered in this research report. However, there are several economic and financial variables which may also impact consumption. In a system that involves several variables, IRFs model a variable's response to an impulse in another variable (impulse response relationship). If one variable Y_t is affected due to an impulse (unpredictable event that affects an economy or innovation) in another variable X_t, then X_t is causal to Y_t.

A $VAR(p)$ process can be represented in the form of a vector moving average (VMA) process

$$\boldsymbol{Y}_t = \sum_{\boldsymbol{i=0}}^{\infty} \boldsymbol{\Psi}_i \, \boldsymbol{\varepsilon}_{t-i} \tag{26}$$

where, $\boldsymbol{\Psi}_0 = \mathbf{I_n}$ and $\boldsymbol{\Psi}_i$ is the i^{th} coefficient matrix of the moving average (MA) representation of a $VAR(1)$ process. The MA coefficient matrices contain the impulse responses of the system. The impulse-response function is defined as

$$\boldsymbol{Y}_{t+n} = \sum_{\boldsymbol{i=0}}^{\infty} \boldsymbol{\Psi}_i \, \boldsymbol{\varepsilon}_{t+n-i} \tag{27}$$

where $\{\boldsymbol{\Psi_n}\}_{i,j} = \frac{\partial Y_{i,t+n}}{\partial Y_{j,t}}$ represents the one-time impulse in $Y_{j,t}$ and the response $Y_{i,t+n}$ which follows. This is assessed with all other variables in the system at period t or earlier held constant. A unit impulse in variable j and the response variable i is plotted on a graph to view the active interrelationships between the variables of the system. The responses to impulses are zero when one of the variables does not result in the Granger causality of the other variables taken in group (*Rossi, 2009*).

A problematic assumption in impulse response analysis is that a shock occurs only in one variable at a time. Such an assumption may be reasonable if the shocks in different variables are independent. If the variables are not independent, then the error terms may consist of all the influences of variables that are not directly included in the set of VECM model. Alternatively, errors that are correlated could be an indication that an impulse to one variable may be followed by an impulse to another variable. To handle these two problems, the responses of impulses is analysed using the Moving Average representation called Cholesky decomposition ($\boldsymbol{\Omega} = \boldsymbol{PP'}$) where $\boldsymbol{P}$ is a lower triangle (nxn) matrix.

Equation 26 then takes the form

$$\boldsymbol{Y}_t = \sum_{\boldsymbol{i=0}}^{\infty} \ominus_{\boldsymbol{i}} \, \boldsymbol{w}_{\boldsymbol{t-i}} \quad (28)$$

where $\ominus_{\boldsymbol{i}} = \boldsymbol{\Psi}_i \boldsymbol{P}$, $w_t = \boldsymbol{P}^{-\mathbf{1}} \boldsymbol{\varepsilon}_t$ and $E[w_t w_t'] = \mathbf{I_n}$.

A change in one element of $\boldsymbol{w_t}$ has no effect on the other elements as they are uncorrelated. The variances of the elements are one and therefore a single impulse is equivalent to an impulse of size one standard deviation. Elements of $\ominus_{\boldsymbol{i}}$ represent the responses of the system to these impulses. The response on variable j of a single impulse in the k-th variable which occurred i periods ago is represented by $\{\ominus_{\boldsymbol{i}}\}_{jk}$ (*Rossi, 2009*).

Variance decomposition (VDC) assists in interpreting the VAR model after its coefficients have been estimated. It indicates the information each variable contributes to the other variables in the VAR and assists in determining the amount of the forecast error variance of each of the variables which can be explained by external impulses to the other variables. The forecast VDC determines the proportion of the change in Y_{jt} due to the shock ϵ_{jt} versus shocks of other variables ϵ_{it} for $i \neq j$ (*Kozhan, 2009*).

Chapter 3: Literature Review

The idea that changes in consumer and business confidence can be an important driver of economic and financial variables is an old but controversial one. It assumes that confidence reacts not only to movements in economic fundamentals but is itself an independent cause of economic fluctuations distinct from those fundamentals.

The 2007-08 financial crisis and the subsequent recession has given a larger importance to the role of confidence as a key metric for economic development. Households have been found to increase their precautionary savings and, therefore reduce their consumption in reaction to higher uncertainty about their future income. Companies react to uncertainty by reducing capital investment and staff expansion plans. This results in reduced borrowing for capital investment or the purchase of tangible assets (*ECB Monthly Bulletin, January 2013*). Beaudry and Portier (*2006)* observed that during periods of increased confidence there was an expectation of higher productivity. This had substantial effects which included increased consumption, higher investment, real GDP increase, and share prices were pushed higher. Increases in confidence accounts for more than 40% of changes in consumption, investment, and hours worked (*Leduc, 2010*). This behaviour has resulted in the European Central Bank (ECB) finding that confidence indices are beneficial to track economic changes as they are timely and contain leading information relating to economic and financial variables.

Confidence indices, however, do not necessarily imply a causal relationship with economic and financial variables. A common factor, like an economic or financial event (e.g. stock market crash) could explain the co-movements. The ECB have also found that when there are usual periods of economic activity, confidence indices provide minimal information in forecasting economic and financial variables. This was attributed to confidence indices already including information that is contained in economic or financial data. The ECB found that confidence indices contributed more to forecasting during periods of uncertainty which feature substantial changes in economic and financial variables (*ECB Monthly Bulletin, January 2013*).

The evidence from existing research about the association between confidence and confidence measures is mixed but most find that they are significant (*Dees and Brinca, 2011*). Dees and Brinca (2011) assessed the role of confidence in explaining consumption of households. The data of two countries which were evaluated in this study was the United States (U.S) and the European Union (E.U), prior to the Brexit vote in June 2016. The study showed the extent of the additional information confidence indicators brought to the predication of household consumption beyond variables usually found to have explanatory power (e.g. interest rates or wealth). The conditions which confidence indicators could be a good predictor of household consumption was also investigated.

The results showed that in the U.S, confidence is Granger caused by financial wealth and equity prices, while in the E.U, unemployment rates, interest rates and foreign confidence are the only variables that Granger cause domestic confidence. The causality analysis was extended with a simple model where the change in consumption only depends on the change in confidence indicators. This analysis found that U.S confidence indicators did not Granger cause consumption expenditure but U.S confidence did Granger cause E.U consumption.

Additionally, Dees and Brinca (2011) estimated a VAR model to analyse the impact a shock to confidence on consumption using impulse response functions. A shock to confidence was found to have an impact on consumption for E.U which was short term significant, while the U.S has no long run significant association between confidence and consumption growth. The analysis also found that shocks in economic and financial variables play a relatively larger role on average relative to shocks in confidence on consumption.

The study by Dees and Brinca (2011) also raised an important caveat regarding the measurement of confidence indices. These indices are a subjective assessment of respondents to their circumstances and environment. Indices also suffer measurement error as survey questions may be ambiguous. As was done in previous research, confidence indices determined using survey data were regarded as adequate proxies of consumers’ perceptions about the economic environment and could be used as predictor variables of consumption.

Özerkek and Çelik (2010) investigated the importance of consumer confidence and attempted to understand its relationship with fiscal spending and consumer consumption for emerging market countries. The first objective which was examined looked at whether a change in consumer confidence could give rise to a change in fiscal spending. The second objective was to determine whether fiscal spending and consumer consumption are determinants of consumer confidence.

The study by Özerkek and Çelik (2010) found that a long run relationship existed between the three variables. The study found that when consumer confidence increased then households were optimistic that economic conditions would increase in the future, and the consumption of consumers increases. A rise in private consumption was found to have resulted in businesses leading the economic cycle and government reducing the need to stimulate the economy. Özerkek and Çelik (2010) further found that the relationship between government spending and consumer consumption is highly influenced by the level of confidence consumers have in an economy. The study also concluded that in a dynamic world of information flows, economic agents should not fail to incorporate confidence expectations into consumption decisions.

Khumalo (2014) used quarterly South African data to determine from a consumer perspective if any long run relationship existed between expenditure and confidence. He also included growth of GDP in the paper which was used as a variable to signify economic growth. The variables were found to be cointegrated which implied the existence of a long run relationship between them. He found that consumer confidence and economic growth affect consumer expenditure positively which results in increased expenditure in the economy. At most one cointegration vector was found between the variables. The VECM found that consumer expenditure adjusts towards equilibrium by thirty eight percent between quarters. The IRFs also supported the results of a positive relation between consumer expenditure and confidence. The study by Khumalo (2014) found consumer confidence had a positive and significant effect on consumer expenditure from a South African perspective. It also recommended that policy makers should take this outcome into consideration.

Other studies which have also tried to establish this link include Fuhrer (1993), Carroll et al. (1994), Bram and Ludvigson (1998), Ludvigson (2004), Souleles (2004) and Lahiri et al (2012) with mixed outcomes. Fuhrer (1993) showed that consumer confidence does not cause economic conditions such as levels of income growth, inflation, unemployment, and interest rates but rather reflect these conditions. Carroll et al. (1994) showed evidence that the lagged consumer confidence had some explanatory power for changes in household consumption. Bram and Ludvigson (1998) found that confidence data from difference universities had different economic and statistical significance on the prediction of consumer consumption. This is an indication of the subjectivity of the confidence index. Ludvigson (2004) showed evidence that confidence indicators contain some information about future consumer consumption growth but most of the information is also inherent in economic and financial indicators. He concluded that confidence indicators assist minimally in the prediction of consumer consumption. Souleles (2004) showed evidence that confidence does help in forecasting consumption growth. Lahiri et al (2012) found that confidence played a key role in improving the accuracy of consumption forecasts. They also found during the recession of 2007–2009, sentiment had a more pervasive effect on aggregate consumption.

The studies by Dees and Brinca (2011), Özerkek and Çelik (2010) and Khumalo (2014) also found that including confidence when modelling outcomes may or may not improve forecasting results. “Animal Spirits” (*Keynes, 1936*) describes the irrational and non-economic motives of people which results in economic fluctuations. The results of this research report may therefore not necessarily find sentiment to have a relationship with consumption.

Chapter 4: Methodology

This section outlines the steps to be followed to achieve the stated objectives. The existence of associations will be considered for the following 3 cases:

i. consumer consumption and consumer confidence,
ii. business consumption and business confidence, and
iii. business confidence and consumer confidence.

The data will be analysed using EViews 9 which is an econometric software commonly used for time series analysis. The analysis will begin by attempting to understand the data using timeseries plots of the following variable pairs:

a) change in consumer confidence and the change in household consumption;
b) the change in business confidence and the change in capital formation; and
c) the change in business confidence and the change in consumer confidence.

These time series plots assist in determining if relationships between the variables can be identified visually. It will also assist in identifying issues with structural breaks.

Formal tests will be conducted next to determine if structural breaks exist and the period in which they exist. This will ensure that any relationships identified in this research report do not suffer from specification issues. The Augmented Dickey-Fuller tests, discussed in Section 2.3.3, will be performed thereafter to determine the integration order of the variables in the research report.

Specifying a smaller lag length or using the incorrect deterministic components may affect model performance. The lag length will therefore need to be determined using AIC or SBC selection criteria. For the variable pairs under consideration to Granger cause each other (in either direction), they must be cointegrated. Several methods will be used to identify if the series are indeed cointegrated. These include:

i. expert knowledge and economic theory about the data,
ii. plotting the various series and
iii. inspecting if there is a common stochastic trend or by performing statistical tests for cointegration.

The Johansen procedure, discussed in Section 2.4.2, will be used to determine if a long run relationship exists between the variable pairs.

An appropriate error correction model (equations 30, 32, 34, 36, 38 and 40) with the appropriate deterministic components (i.e. no deterministic components, a constant and no trend term, constant and trend term) will be specified and estimated to understand the short and long run behaviour of the pair of variables. The residuals of these models will be analysed using the Jarque-Bera test for normality and the Breusch–Godfrey serial correlation LM test. The Jarque-Bera test for normality tests if the residuals have a normal distribution with zero skewness and excess kurtosis. It is tested against the alternative hypothesis that the residuals have a non-normal distribution. The analysis of the residual diagnostics ensures that the residuals are white noise, i.e. the residuals do not have autocorrelation inherent.

Granger causality tests, outlined in Section 2.5, will be used to analyse the association between confidence and consumption. There are three possible outcomes (*Awe, 2012*) from these tests:

i. unidirectional causality where there is a one direct causality between the pair of variables;
ii. bidirectional causality where both variables cause each other, and
iii. no causality.

Granger causality provides an understanding about causal relationships between variables. It is often of interest to know the response of dependent variable to an impulse in an independent variable of a system that involves several other economic variables as well. This research report will also analyse this type of causality using VDC and IRFs. The VDC of each of the variables will be calculated and plotted to understand the amount of the forecast error which can be explained by exogenous shocks to one of the variable pairs. IRFs will be used to analyse the responsiveness of the dependent variables in the $VECM$ when a dependent variable in the model receives an impulse. Conclusions regarding the outcome of the tests and analysis will be made thereafter.

Chapter 5: Data Analysis and Results

The following notation will be introduced to represent the variables in this analysis: CCI_t (Consumer confidence index at time t); HC_t (Household consumption at time t); BCI_t (Business Confidence index at time t) and CF_t (Capital Formation at time t).

5.1 Time Series Plot of the Data

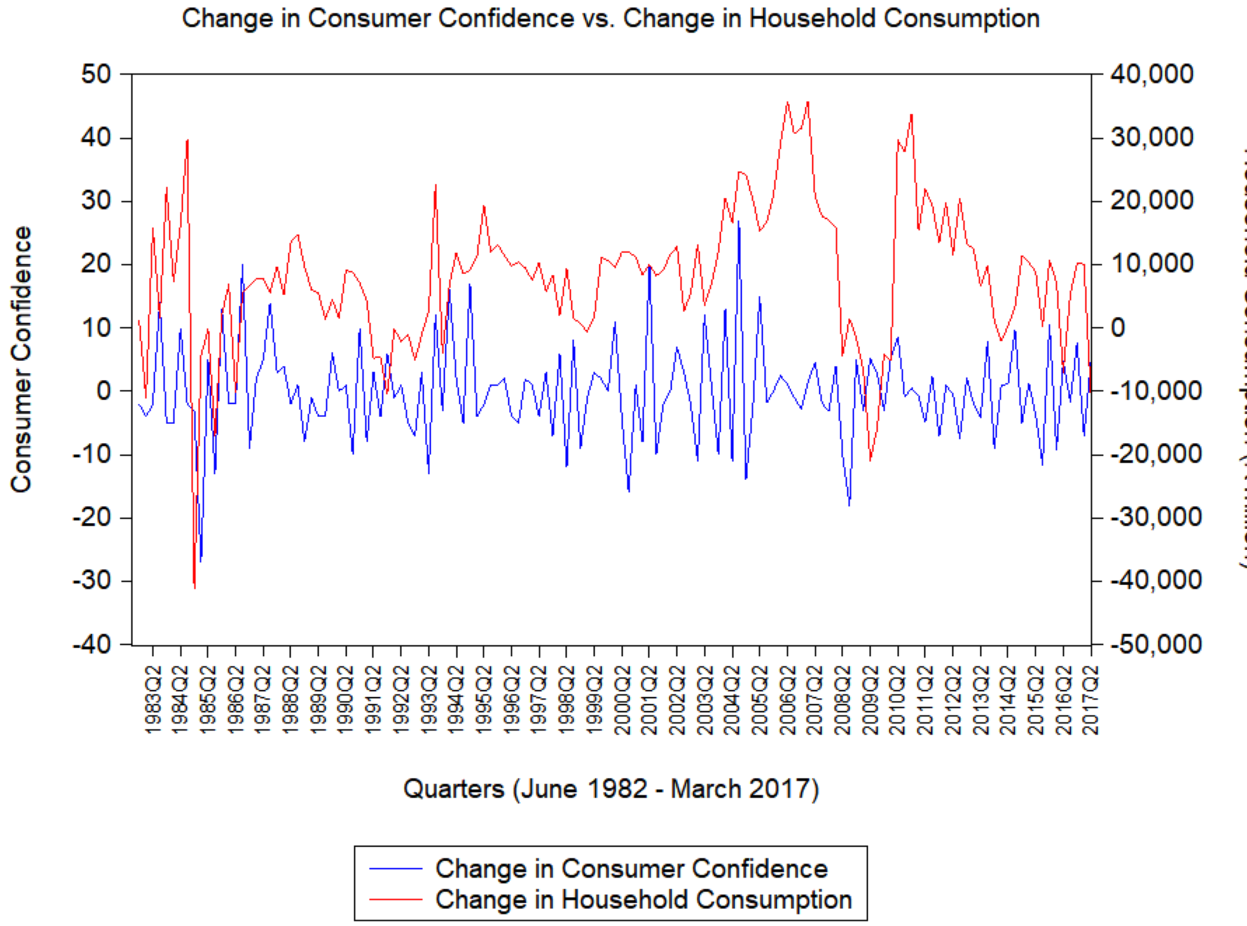

Figure 5.1: Co-movement between changes in consumer confidence and changes in household consumption

There are crucial events in South Africa's history which may be observable in the time series plot of the data between June 1982 and March 2017. In 1985, confidence and consumption lows were experienced due to the country being in a state of emergency when hundreds of people were killed in political violence and thousands were detained in the ensuing year. The official start of the process of ending apartheid and unbanning of organisations that were banned by the government including the African National Congress, the South African Communist Party and the Pan Africanist Congress began in 1990. Political prisoners including Nelson Mandela were also released. Ahead of the historic democratic elections, in 1993 South Africans lived in fear of civil war and popular leader Chris Hani was assassinated. The Truth and Reconciliation Commission began its formal hearings in 1996 to assist in dealing with the violence and human rights abuses during apartheid. The constitution was amended by the Constitutional Assembly and new agreements relating to culture, taxation and tax evasion and defence equipment were also signed.

Between 1998 and 2001, the South African rand was in crisis mode due to exchange rate overshooting which was possibly influenced by the peak of the AIDS pandemic at the time. South Africa had its third democratic election in 2004 and Nelson Mandela retired. The global financial crisis and recession began in 2008, and its effects lasted 3 years. South Africa hosted the soccer World Cup in 2010 and 20 million working days (determined by number of participants multiplied by the length of stoppage) lost during strikes (*Mail and Guardian, 2012*). In 2014 there was a one-month long strike by Numsa members (*Mail and Guardian, 2014*). Political and economic turmoil in 2015 was further exacerbated by political battles between Jacob Zuma and previous finance minister Pravin Gordhan; the president's decision to reshuffle finance ministers the fourth time in his term and the calls for the president to step down amid corruption scandals (*Chutel, 2017*). It is expected that events with negative consequences will reduce the outlook of consumers and businesses about the future. As per the definition of consumer and business confidence, this will result in a lower confidence index. The opposite effect will be experience when there is a positive outlook about the future.

Figure 5.1 does show periods where consumer confidence and consumer consumption follow similar paths. In 2005, there appears to be a larger increase in household consumption and incremental changes in confidence. This was after the 3rd democratic election. However, a different trend is visible prior to the 2008 financial crisis where there is a large increase in consumption despite a small increase in confidence. This increase in consumption however did seem to normalise to historical trends in 2014. Apart from these large deviations, it does appear that changes in household consumption do trigger changes in confidence.

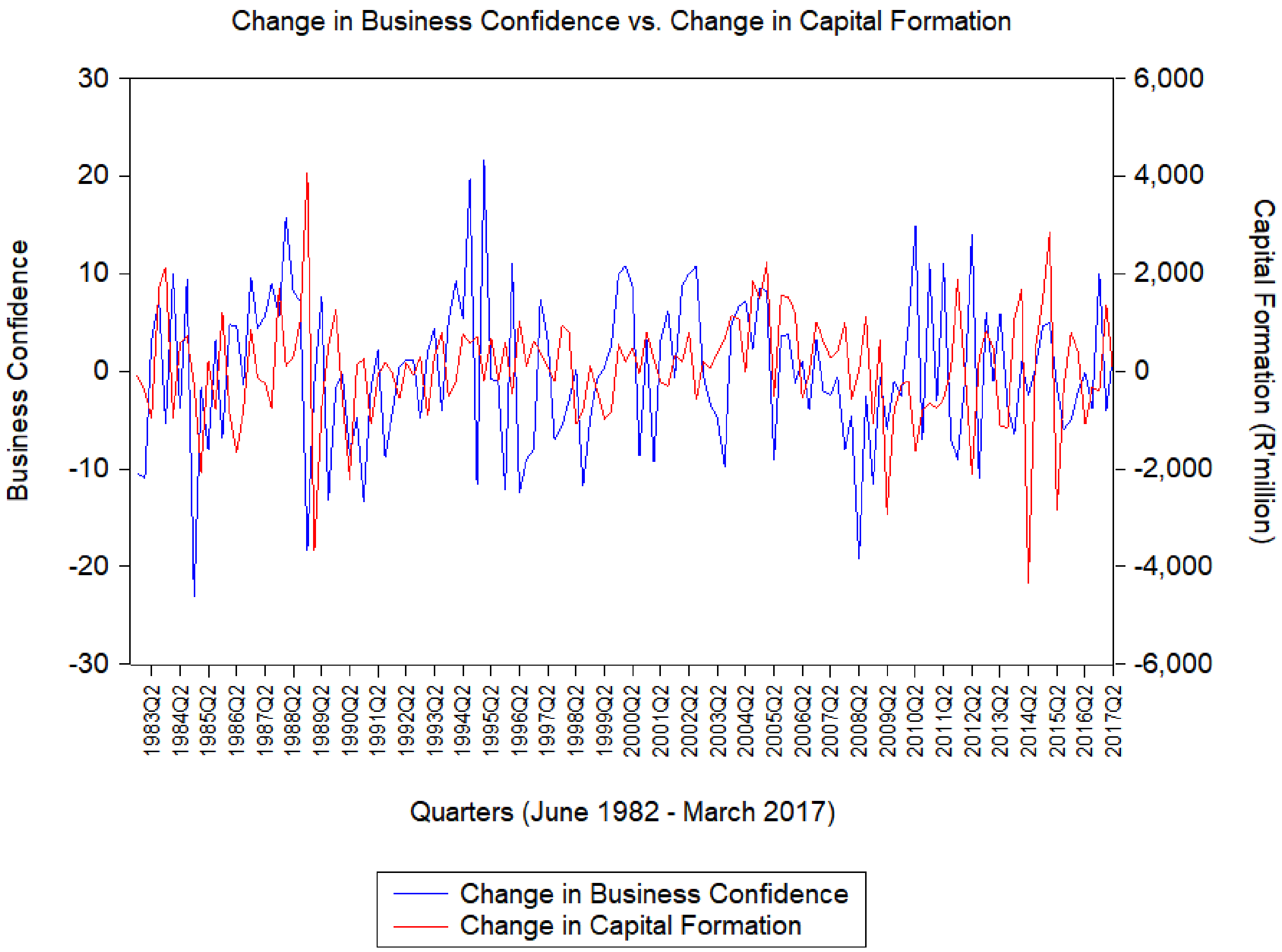

Figure 5.2: Co-movement between changes in business confidence and changes in capital formation

It does show periods where business confidence and capital formation follow similar paths (pre 1994 elections and after 2004 to before the 2008 financial crisis), but there are also periods in which business confidence has larger swings for incremental changes in capital formation (post the 1994 elections to prior to 2004, and prior to the 2008 financial crisis). Post 2013, the trend appears to have changed where capital formation has larger swings than business confidence which could have been a result of strikes and Jacob Zuma cabinet reshuffle.

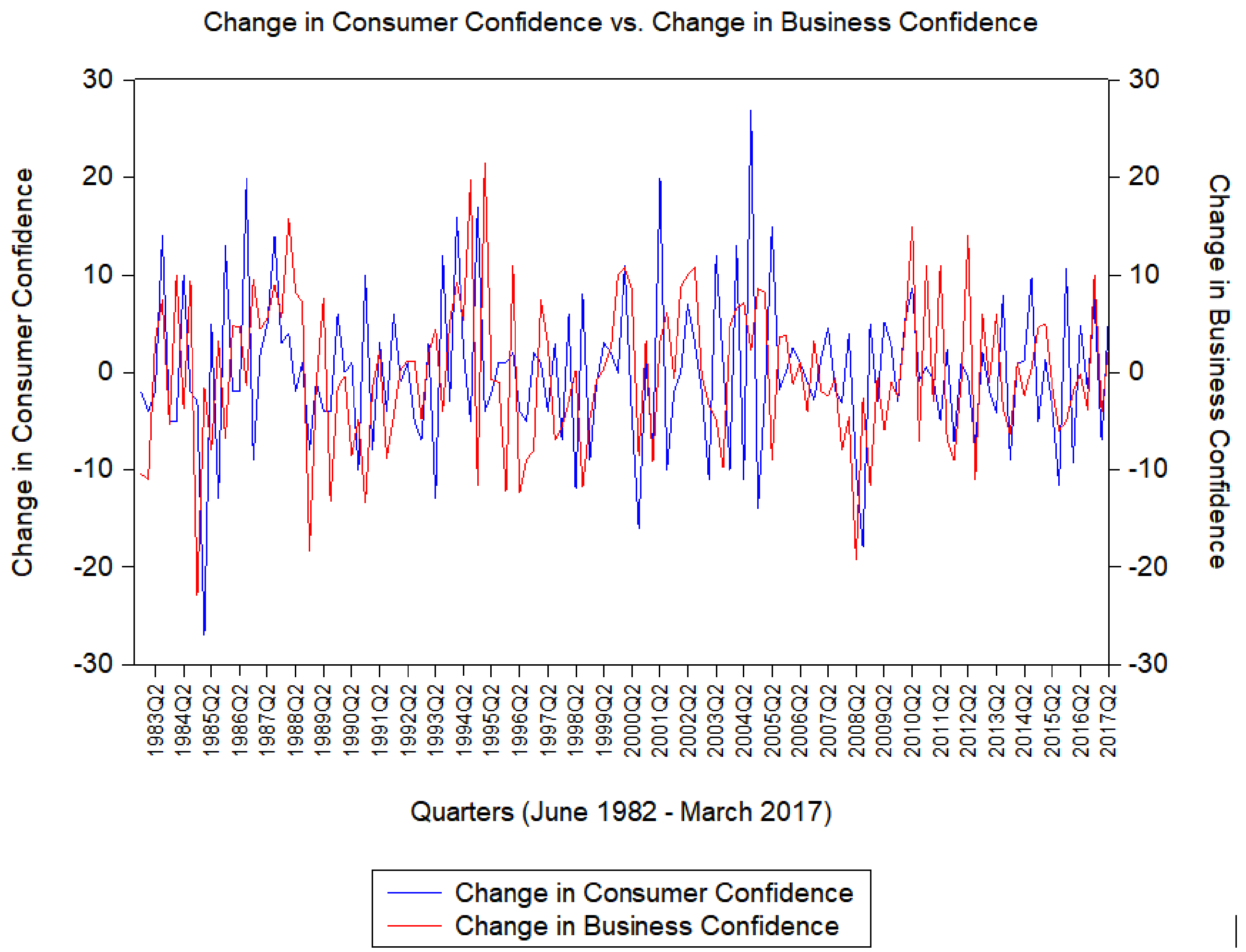

Figure 5.3: Co-movement between changes in business confidence and changes in consumer confidence

Business confidence and consumer confidence largely follow similar paths in figure 5.3 post the 2008 financial crisis. There does seem to be larger swings in business confidence than consumer confidence between 1987 and prior to the 2008 financial crises. This suggests that businesses were more reactive than consumers prior to the financial crises. Apart from this outlier, the time series seem to follow similar paths.

Overall, the three pairs of variables above do show some form of co-movement but there are also periods where the paths deviate. Structural breaks in the data will be tested next to determine if dummy variables will need to be included in the model formation owing to the discussed significant points in South Africa's history.

5.2 Testing for Structural Breaks

Structural breaks occur when the coefficients of the time series model changes over the period being considered for the analysis. These coefficients will not be valid in the short and long run. The diagnostic checks for models with breaks which arise due to exogenous shocks may also show that the residuals are not normally distributed. These may be the result of unforeseen political changes (e.g. cabinet reshuffles), stock market crashes (e.g. 2008 financial crisis) and wars in countries which impact commodity prices (e.g. Gulf war). (Feridun, 2009).

Multiple breakpoints at a 5% significance level were tested using the Bai-Perron tests of $(l+1)\ versus.\ l$ sequentially. The Bai-Perron methodology has two parts, the first one identifies any number of breaks in a time series, regardless of statistical significance and the second proposes a series of statistical tests to test for the statistical significance of these breaks, using asymptotic critical values (Antoshin et al, 2008). This test is used in a sequential way to estimate consistently the number of changes in a set of data. The test statistic is based on the difference between the optimal sum of squared residuals associated with l breaks and the optimal sum of squared residuals associated with $(l+1)$ breaks (Jouini and Boutahar, 2005). Table 5.1 provides a summary of breakpoints identified with the R^2 and Adjusted R^2 providing an indication of the fit of the model with the inclusion of breaks. The detailed results can be found in Appendix B: Stability tests.

Table 5.1: Structural Breaks

Dependent Variable	Independent Variable	No. of Breaks	Break Dates	R^2	Adjusted R^2
HC_t	CCI_t	4	6/01/1988 6/01/1995 6/01/2004 3/01/2010	75.19%	73.47%
CCI_t	HC_t	3	3/01/1998 6/01/2004 6/01/2010	42.94%	39.91%
CF_t	BCI_t	3	6/01/1996 12/01/2004 3/01/2010	68.11%	66.41%
BCI_t	CF_t	4	9/01/1987 6/01/1996 12/01/2001 3/01/2008	55.83%	52.78%
BCI_t	CCI_t	3	9/01/1990 12/01/2001 3/01/2008	62.94%	60.97%
CCI_t	BCI_t	5	3/01/1988 9/01/1994 12/01/1999 3/01/2005 3/01/2012	71.30%	68.83%

Notes: Dummy variables will be introduced to handle for the structural breaks identified above. These are in arranged in chronological order. The dummy variable is 1 from one break period to another and 0 thereafter. $DVCC_t^1$, $DVCC_t^2$, $DVCC_t^3$ and $DVCC_t^4$ for the 4 structural breaks identified in the relationship between CCI_t and HC_t; $DVCH_t^1$, $DVCH_t^2$ and $DVCH_t^3$ for the 3 structural breaks identified in the relationship between HC_t and CCI_t; $DVBC_t^1$, $DVBC_t^2$ and $DVBC_t^3$ for the 3 structural breaks identified in the relationship between BCI_t and CF_t; $DVCF_t^1$, $DVCF_t^2$, $DVCF_t^3$ and $DVCF_t^4$ for the 4 structural breaks identified in the relationship between CF_t and BCI_t; $DVCB_t^1$, $DVCB_t^2$ and $DVCB_t^3$ for the 3 structural breaks identified in the relationship between BCI_t and CCI_t; and $DVBCC_t^1$, $DVBCC_t^2$, $DVBCC_t^3$, $DVBCC_t^4$ and $DVBCC_t^5$ for the 5 structural breaks identified in the relationship between CCI_t and BCI_t.

The break points identified above are closely related to events identified earlier in South Africa's past. These were further verified in the plots of the data. The events which appear prevalent as break points above are the 2008-2010 Financial Crisis, 2010 World Cup, the 2004 democratic elections, and the period between 1985 state of emergency to 1990 beginning to unban political parties. Dummy variables will be used to capture these shocks to improve model fit. The dummy variables will be set to equal zero for all observations except the period(s) in which a shock occurred where it will have a value one. Dummy variables included in the model should assist in ensuring that model residuals do not suffer from autocorrelation and heteroscedasticity (*Feridun*, *2009*).

5.3 Testing for Stationarity and Detecting Integration Order of the Variables

Stationarity tests are first performed to determine if the variables are stationary and thereafter the integration order of the variables will be determined. Structural breaks which were suspected in figures 5.1, 5.2 and 5.3, were confirmed in the breakpoint tests in Table 5.1. Unit root tests are run considering the presence of these structural breaks to prevent obtaining test results which are possibly biased towards non-rejection of the null hypothesis of a unit root. Many of the changes in government policy or global economics are sudden rather than gradual changes. An additive outliers (AO) model is more appropriate for this model as it captures sudden changes in the mean of a series. The Dickey Fuller minimum t test breakpoint selection, which is an application of the Perron's unit root test to handle for structural breaks is applied. The trend and break point specification were based on the intercept only. The lag length was selected based on the Schwarz information criterion (see Table 5.14).

Table 5.2 reports the results of the unit root tests. The null hypothesis $H_0: \gamma = 0$ (Y_t a unit root with structural break(s) in the series) is tested against the alternative $H_1: \gamma < 0$ (Y_t is stationary with break(s)).

Table 5.2: ADF Test Results with no differencing

Variable	ADF Test Statistics	At 99% Critical level	Vogelsang (1993) asymptotic one-sided *p*-values
HC_t	-1.598789	-4.949133	> 0.99
CCI_t	-3.514597	-4.949133	0.3789
CF_t	-3.858679	-4.949133	0.2106
BCI_t	-3.088742	-4.949133	0.6342

Looking at the *p*-values, the null hypothesis cannot be rejected and therefore all 4 variables have each a unit root. The first difference of the variables will be considered next to determine if the variables will become stationary.

Table 5.3: ADF Test Results with differencing of order 1

Variable	ADF Test Statistics	At 99% Critical level	At 95% Critical level	Vogelsang asymptotic one-sided p-values	Order of Integration
ΔHC_t	-6.930298	-4.949133	-4.443649	< 0.01	$I(1)$
ΔCCI_t	-18.60499	-4.949133	-4.443649	< 0.01	$I(1)$
ΔCF_t	-4.452339	-4.949133	-4.443649	0.0490	$I(1)$
ΔBCI_t	-12.39275	-4.949133	-4.443649	< 0.01	$I(1)$

Notes: Notation is introduced in the above table for the variables in the first difference: ΔCCI_t (Change in consumer confidence index at time t); ΔHC_t (Change in household consumption at time t); ΔBCI_t (Change in business Confidence index at time t) and ΔCF_t (Change in capital Formation at time t).

Looking at the *p*-values for the first difference, the null hypothesis can be rejected for the first difference of all the variables at the 5% level. Since the integration order of the variables under consideration is the same, *I(1)* in this case, then the variables may potentially be cointegrated. The lag lengths are required for cointegration testing and will be determined next.

5.4 Lag Length Selection

The lag length can be determined using several information criteria estimators. These include:

- Sequential modified LR test statistic (*LR*),
- Final prediction error (*FPE*),
- Akaike information criterion (*AIC*),
- Schwarz information criterion (*SBC*) and
- Hannan-Quinn information criterion (*HQ*).

As per the theory discussed earlier, the results of AIC and SBC will be used to determine the optimal lag length.

Table 5.4 provides a summary of the Information criteria results and lags selected for each pair of variables. The detailed results of information criteria tests for each of pair of variables considered can be found in Appendix C: Lag Length Selection.

Table 5.4: Lag Length Selection

Dependent Variable	Independent Variable	Exogenous Variables	AIC	SBC	Optimal Lag
HC_t	CCI_t	$DVCC_t^1$ $DVCC_t^2$ $DVCC_t^3$ $DVCC_t^4$	27.84077	28.23388	2
CCI_t	HC_t	$DVCH_t^1$ $DVCH_t^2$ $DVCH_t^3$	27.84049	28.18992	2
CF_t	BCI_t	$DVBC_t^1$ $DVBC_t^2$ $DVBC_t^3$	23.6529	23.91497	1
BCI_t	CF_t	$DVCF_t^1$ $DVCF_t^2$ $DVCF_t^3$ $DVCF_t^4$	23.67239	23.97814	1
BCI_t	CCI_t	$DVCB_t^1$ $DVCB_t^2$ $DVCB_t^3$	13.4172	13.76663	2
CCI_t	BCI_t	$DVBCC_t^1$ $DVBCC_t^2$ $DVBCC_t^3$ $DVBCC_t^4$ $DVBCC_t^5$	13.47224	13.82167	1

The lags identified in Table 5.4 show that households are unlikely to change consumption behaviour too quickly (2 lags) due to changes in consumer confidence and are likely to wait up to half a year (quarterly data) before reacting. In contrast, businesses appear to be more reactive (1 lag) to changes in capital expenditure as business confidence changes. This could be linked to businesses having to remain relevant and ahead of competitors. The confidence of businesses also appears to be more reactive to changes in consumer confidence than the confidence of consumers to changes in business confidence.

5.5 Cointegration Analysis

The Johansen cointegration test is more appropriate as it allows for testing of hypotheses when dummy variables need to be considered in the model, which could not be done with the Engle-Granger methodology. The 2-step Johansen cointegration methodology described earlier will be followed. The dummy variables for the pairs of variables identified earlier have been included as exogenous variables in the model.

5.5.1 Household Consumption predicted by Consumer Confidence

In the first step, cointegrating relationship is analysed where HC is the dependent variable, CCI is a predictor variable and the exogenous variables $DVCC_t^1$, $DVCC_t^2$, $DVCC_t^3$ and $DVCC_t^4$ are the 4 structural breaks. The results for the Trace test (TT) and Maximum Eigenvalue (ME) tests are given in Table 5.5 with the statistic applicable to each test, the Critical Value (CV) and p-Value (derived from MacKinnon-Haug-Michelis (1999)). The first column is the hypothesis testing the number cointegrating equation(s) (CE(s)) which exist.

Table 5.5: Cointegration Tests: $\boldsymbol{HC}$ predicted by $\boldsymbol{CCI}$

Number of CE(s)	Eigen value	TT			ME		
		Statistic	5% CV	p-Value	Statistic	5% CV	p-Value
None *	0.179992	27.53463	12.32090	0.0001	27.18650	11.22480	0.0000
At most 1	0.002538	0.348126	4.129906	0.6179	0.348126	4.129906	0.6179

The null hypothesis of no cointegrating vector is rejected using both tests and finds $r = 1$ (one cointegrating vector) at a 5% level between HC and CCI. In the second step, the matrix of cointegrating coefficients $\boldsymbol{\beta}'$ from fitting the error correction model in equation (7), is determined to be:

$$\boldsymbol{\beta}' = \begin{bmatrix} 1.27\text{E}-06 & 0.141268 \\ 2.78\text{E}-06 & -0.004791 \end{bmatrix}.$$

Similarly, the matrix of error correction coefficients measuring the speed of convergence to the long run equilibrium is:

$$\boldsymbol{\alpha} = \begin{bmatrix} 1134.127 & 443.6557 \\ -2.720797 & 0.160092 \end{bmatrix}.$$

It is determined that the coefficient of CCI, in the time series model (29), to predict HC in the long run is 111286.6. This coefficient indicates that as CCI increases in the long run, HC will increase. Similarly, the adjustment coefficient is calculated to be 0.001440. A value between 0 and -1 is an indication of the convergence of the series in the next lag period. A positive adjustment coefficient implies that the process is not converging in the long run and there may be some instabilities. This output implies there could be model specification problems by only including CCI as the dependent variable.

5.5.2 Consumer Confidence predicted by Household Consumption

Since the causal direction is not known in advance, the roles of the variables are reversed. That is, CCI is now the dependent variable while HC is the predictor variable and the exogenous variables $DVCH_t^1$, $DVCH_t^2$ and $DVCH_t^3$ are the 3 structural breaks. The results for the Trace test (TT) and Maximum Eigenvalue (ME) tests are given in Table 5.6 with the statistic applicable to each test, the Critical Value (CV) and *p*-Value (derived from MacKinnon-Haug-Michelis (1999)).

Table 5.6: Cointegration Tests: CCI predicted by HC

Number of CE(s)	Eigen value	TT			ME		
		Statistic	5% CV	*p*-Value	Statistic	5% CV	*p*-Value
None *	0.202733	34.64232	12.32090	0.0000	31.03949	11.22480	0.0000
At most 1	0.025955	3.602831	4.129906	0.0684	3.602831	4.129906	0.0684

The null hypothesis of no cointegrating vector is rejected using both tests and finds $r = 1$ (one cointegrating vector) at a 5% level between CCI and HC.

The matrix of cointegrating coefficients is:

$$\boldsymbol{\beta}' = \begin{bmatrix} -0.137914 & -7.03\text{E}-07 \\ 0.025061 & -1.70\text{E}-06 \end{bmatrix}.$$

The matrix of error correction coefficients measuring the speed of convergence to the long run equilibrium is:

$$\boldsymbol{\alpha} = \begin{bmatrix} 2.746739 & -0.600544 \\ -1592.017 & -1391.208 \end{bmatrix}.$$

The coefficient of HC in the time series model (31) to predict CCI in the long run is 5.10E-06 which indicates that as HC increases in the long run, CCI will increase. The adjustment coefficient is -0.378814 which indicates that the deviation from the long-term growth in CCI is corrected by 37.88% in the next quarter.

5.5.3 Capital Formation predicted by Business Confidence

The cointegrating relationship of business variables is analysed next. In this first case, CF is the dependent variable, BCI is a predictor variable and the exogenous variables $DVBC_t^1$, $DVBC_t^2$ and $DVBC_t^3$ are the 3 structural breaks. The results for the Trace test (TT) and Maximum Eigenvalue (ME) tests are given in Table 5.7 with the statistic applicable to each test, the Critical Value (CV) and *p*-Value (derived from MacKinnon-Haug-Michelis (1999)).

Table 5.7: Cointegration Tests: CF predicted by BCI

Number of CE(s)	Eigen value	TT			ME		
		Statistic	5% CV	*p*-Value	Statistic	5% CV	*p*-Value
None *	0.135208	20.05501	12.32090	0.0021	20.04670	11.22480	0.0011
At most 1	6.02E-05	0.008306	4.129906	0.9406	0.008306	4.129906	0.9406

The null hypothesis of no cointegrating vector is rejected using both tests and finds $r = 1$ (one cointegrating vector) at a 5% level between CF and BCI.

The matrix of cointegrating coefficients is:

$$\boldsymbol{\beta}' = \begin{bmatrix} -0.000169 & 0.061823 \\ 9.15\text{E}-05 & 0.005834 \end{bmatrix}.$$

The matrix of error correction coefficients measuring the speed of convergence to the long run equilibrium is:

$$\boldsymbol{\alpha} = \begin{bmatrix} 376.8436 & 3.038013 \\ -1.084207 & 0.053907 \end{bmatrix}.$$

The coefficient of BCI in the time series model (33) to predict CF in the long run is -366.3454 which indicates that as BCI increases, CF will decrease in the long run. This result seems unlikely and could be an indication that other variables need to be included in the model specification to predict CF. The adjustment coefficient is -0.063594. This indicates that deviation from the long-term growth in CF is corrected by 6.36% in the next quarter. The small adjustment coefficient also indicates there may be additional variables with more information which are involved in the prediction of CF.

5.5.4 Business Confidence predicted by Capital Formation

The roles of the business variables are reversed next. That is, BCI is the dependent variable, CF is a predictor variable and the exogenous variables $DVCF_t^1$, $DVCF_t^2$, $DVCF_t^3$ and $DVCF_t^4$ are the 4 structural breaks. The results for the Trace test (TT) and Maximum Eigenvalue (ME) tests are given in Table 5.8 with the statistic applicable to each test, the Critical Value (CV) and p-Value (derived from MacKinnon-Haug-Michelis (1999)).

Table 5.8: Cointegration Tests: BCI predicted by CF

Number of CE(s)	Eigen value	TT			ME		
		Statistic	5% CV	p-Value	Statistic	5% CV	p-Value
None *	0.142547	24.86402	12.32090	0.0003	21.22284	11.22480	0.0007
At most 1	0.026040	3.641177	4.129906	0.0669	3.641177	4.129906	0.0669

The null hypothesis of no cointegrating vector is rejected using both tests and finds $r = 1$ (one cointegrating vector) at a 5% level between BCI and CF.

The matrix of cointegrating coefficients is:

$$\boldsymbol{\beta}' = \begin{bmatrix} -0.080111 & 0.000152 \\ 0.007356 & -0.000160 \end{bmatrix}.$$

The matrix of error correction coefficients measuring the speed of convergence to the long run equilibrium is:

$$\boldsymbol{\alpha} = \begin{bmatrix} 2.232254 & 0.775574 \\ -276.9439 & 125.6688 \end{bmatrix}.$$

The coefficient of CF in the time series model (35) to predict BCI in the long run is -0.001898. This indicates that as CF increases, BCI will decrease in the long run. Similar to the results in Section 5.5.3, this result seems unlikely and could be an indication that additional variables need to be included in the model specification to predict BCI. The adjustment coefficient is -0.178828. This indicates that deviation from the long-term growth rate in BCI is corrected by 17.88% in the next quarter. The small adjustment coefficient also indicates there may be other variables with more information which are involved in the prediction of BCI.

5.5.5 Business Confidence predicted by Consumer Confidence

The cointegrating relationship between the confidence variables is analysed next. In this first case, BCI is the dependent variable, CCI is a predictor variable and the exogenous variables $DVCB_t^1$, $DVCB_t^2$ and $DVCB_t^3$ are the 3 structural breaks. The results for the Trace test (TT) and Maximum Eigenvalue (ME) tests are given in Table 5.9 with the statistic applicable to each test, the Critical Value (CV) and p-Value (derived from MacKinnon-Haug-Michelis (1999)).

Table 5.9: Cointegration Tests: BCI predicted by CCI

Number of CE(s)	Eigen value	TT			ME		
		Statistic	5% CV	*p*-Value	Statistic	5% CV	*p*-Value
None *	0.129174	20.45546	12.32090	0.0018	18.94891	11.22480	0.0019
At most 1	0.010936	1.506543	4.129906	0.2576	1.506543	4.129906	0.2576

The null hypothesis of no cointegrating vector is rejected using both tests and finds $r = 1$ (one cointegrating vector) at a 5% level between BCI and CCI.

The matrix of cointegrating coefficients is:

$$\boldsymbol{\beta}' = \begin{bmatrix} 0.010029 & 0.094766 \\ 0.042156 & -0.063588 \end{bmatrix}.$$

The matrix of error correction coefficients measuring the speed of convergence to the long run equilibrium is:

$$\boldsymbol{\alpha} = \begin{bmatrix} -2.026627 & -0.426538 \\ -1.907073 & 0.459083 \end{bmatrix}.$$

The coefficient of CCI in the time series model (37) to predict BCI in the long run is 9.449097 which indicates that as CCI increases, BCI will increase in the long run. The adjustment coefficient is -0.020325 which indicates that deviation from the long-term growth in BCI is corrected by 2.03% in the next quarter. The small adjustment coefficient indicates there may be additional variables with more information which are involved in the prediction of BCI.

5.5.6 Consumer Confidence predicted by Business Confidence

The roles of the business variables are reversed next. That is, CCI is the dependent variable, BCI is a predictor variable and the exogenous variables $DVBCC_t^1$, $DVBCC_t^2$, $DVBCC_t^3$, $DVBCC_t^4$ and $DVBCC_t^5$ are the 5 structural breaks. The results for the Trace test (TT) and Maximum Eigenvalue (ME) tests are given in Table 5.10 with the statistic applicable to each test, the Critical Value (CV) and *p*-Value (derived from MacKinnon-Haug-Michelis (1999)).

Table 5.10: Cointegration Tests: CCI predicted by BCI

Number of CE(s)	Eigen value	TT			ME		
		Statistic	5% CV	*p*-Value	Statistic	5% CV	*p*-Value
None *	0.138992	20.70524	12.32090	0.0016	20.65185	11.22480	0.0009
At most 1	0.000387	0.053380	4.129906	0.8498	0.053380	4.129906	0.8498

The null hypothesis of no cointegrating vector is rejected using both tests and finds $r = 1$ (one cointegrating vector) at a 5% level between CCI and BCI.

The matrix of cointegrating coefficients is:

$$\boldsymbol{\beta}' = \begin{bmatrix} -0.131905 & 0.009171 \\ 0.023036 & -0.048799 \end{bmatrix}.$$

The matrix of error correction coefficients measuring the speed of convergence to the long run equilibrium is:

$$\boldsymbol{\alpha} = \begin{bmatrix} 2.557763 & 0.018498 \\ 0.258386 & 0.141274 \end{bmatrix}.$$

The coefficient of BCI in the time series model (39) to predict CCI in the long run is -0.069526 which indicates that as BCI increases, CCI will decrease in the long run. The adjustment coefficient is -0.337380 which indicates that deviation from the long-term growth in CCI is corrected by 33.74% in the next quarter.

5.6 VECM

This section further explores the relationship between the pairs of variables by specifying VECM; estimating and analysing the VECM coefficients and analysing the residuals.

5.6.1 Household Consumption predicted by Consumer Confidence using a VECM

The $VECM$ is specified with HC as the dependent variable, CCI as the predictor variable and the exogenous variables $DVCC_t^1$, $DVCC_t^2$, $DVCC_t^3$ and $DVCC_t^4$ with no intercepts and trends. The lag length of 2 which was determined in Table 5.4 will be applied. The coefficient of CCI in the time series model to predict HC in the long run was calculated in section 5.5.1. The VECM therefore takes the following form:

$$\widehat{\Delta HC} = C(1) * (HC_{t-1} + 111286.638CCI_{t-1}) + C(2) * \Delta HC_{t-1} + C(3) * \Delta HC_{t-2} + C(4) * \Delta CCI_{t-1} + C(5) * \Delta CCI_{t-2} + C(6) * DVCC_t^1 + C(7) * DVCC_t^2 + C(8) * DVCC_t^3 + C(9) * DVCC_t^4 \quad (29)$$

Table 5.11: VECM Coefficients: HC predicted by CCI

Coefficient	Estimate	SE	*t*-Statistic	*p*-value
$C(1)$	0.00144	0.001025	1.404871	0.1625
$C(2)$	0.321089	0.090231	3.558521	0.0005
$C(3)$	0.203593	0.093648	2.174032	0.0315
$C(4)$	50.05652	130.9204	0.382343	0.7028
$C(5)$	36.06885	117.6911	0.306471	0.7597
$C(6)$	760.7758	1971.251	0.385935	0.7002
$C(7)$	2487.678	1975.846	1.259044	0.2103
$C(8)$	1688.478	3188.949	0.529478	0.5974
$C(9)$	2629.856	2387.26	1.101621	0.2727

Substituting the coefficients in Table 5.11 into the VECM in equation (29) yields:

$$\widehat{\Delta HC} = 0.001(HC_{t-1} + 111286.638CCI_{t-1}) + 0.321\Delta HC_{t-1} + 0.204\Delta HC_{t-2} + 50.057\Delta CCI_{t-1} + 36.069\Delta CCI_{t-2} + 760.776DVCC_t^1 + 2487.678DVCC_t^2 + 1688.478DVCC_t^3 + 2629.856DVCC_t^4 \quad (30)$$

$C(1)$ is the adjustment coefficient for the VECM and is the speed of adjustment towards equilibrium in the long run. The *p*-value of $C(1)$ shows that it is not significant in Table 5.11 at a 5% level and its estimate is non-negative as calculated in section 5.5.1. This indicates that these is no long run cointegrating relationship between CCI and HC. $C(2)$, $C(3)$, $C(4)$ and $C(5)$ are the coefficients of the short-run variables. The *p*-value of these variables are not assessed individually. The Wald test is therefore used to test if a short run relationship exists. That is, if these variables are significantly different from zero. The null hypothesis of the Wald test is such that $C(2) = C(3) = C(4) =$

$C(5) = 0$. The F-statistic from the Wald test is 6.273423 with a *p*-value of 0.0001. Therefore, a short run relationship does exist between HC and CCI as the null hypothesis is rejected at a 5% level which indicates the short run coefficients are significantly different from zero. The coefficients of the variables to handle for breakpoints ($C(7)$, $C(8)$ and $C(9)$) are not significant at a 5% level and this indicates that breakpoints have limited impact on the model. The VECM model has an $R^2 = 32.84\%$ which is low and indicates that the model only explains 32.84% of the variability in HC. Similarly, the Durbin-Watson (DW) statistic in the output was 1.928399. A general rule of thumb is if $R^2 > DW$, then there may be spurious results in the time series model. For this model $DW > R^2$ which indicates the results are not spurious.

The Jarque-Bera statistic is 917.650 with a *p*-value of 0.00000. Consequently, the residuals do not follow a normal distribution. The Breusch–Godfrey test is a test for the existence of autocorrelation in the error terms. For this pair of variables, the null hypothesis of no autocorrelation in the error terms cannot be rejected as the F-statistic for the Breusch-Godfrey test is 0.154428 with a *p*-value of 0.8571.

In summary, this model assists in predicting 32.84% of HC. CCI does not assist in the prediction of HC in the long run but does seem to assist in the prediction in the short run. The residuals of the model do not follow a normal distribution which implies that the results of this model do not appear to be reliable. This outcome supports the results in the cointegration tests which found the adjustment coefficient to be divergent.

5.6.2 Consumer Confidence predicted by Household Consumption VECM

The $VECM$ is specified with CCI as the dependent variable, HC as the predictor variable and the exogenous variables $DVCH_t^1$, $DVCH_t^2$ and $DVCH_t^3$, and with no intercepts and trends. The lag length of 2 which was determined earlier in Table 5.4 will be applied. The coefficient of HC for the time series model to predict CCI in the long run was calculated in section 5.5.2. The VECM will therefore take the following form:

$$\widehat{\Delta CCI} = C(1) * (CCI_{\,t-1} + 0.000005 * HC_{t-1}) + C(2) * \Delta CCI_{\,t-1} + C(3) * \Delta CCI_{t-2} + C(4) * \Delta HC_{t-1} + C(5) * \Delta HC_{t-2} + C(6) * DVCH_t^1 + C(7) * DVCH_t^2 + C(8) * DVCH_t^3 \quad (31)$$

Table 5.12: VECM Coefficients: CCI predicted by HC

Coefficient	Value	SE	*t*-Statistic	*p*-value
$C(1)$	-0.378814	0.080146	-4.726542	0.0000
$C(2)$	-0.209964	0.091846	-2.286037	0.0239
$C(3)$	0.078735	0.083119	0.947250	0.3453
$C(4)$	0.000205	6.48E-05	3.170895	0.0019
$C(5)$	3.28E-05	6.72E-05	0.487557	0.6267
$C(6)$	-1.060655	1.474227	-0.719466	0.4732
$C(7)$	4.350350	1.866601	2.330626	0.0213
$C(8)$	-0.226195	1.480250	-0.152809	0.8788

Substituting the coefficients in Table 5.12 into the VECM in equation (11) yields:

$$\widehat{\Delta CCI} = -0.379(CCI_{t-1} + 0.000005 * HC_{t-1}) - 0.21 * \Delta CCI_{t-1} + 0.079\Delta CCI_{t-2} + 0.0002\Delta HC_{t-1} + 0.00003\Delta HC_{t-2} - 1.061DVCH_t^1 + 4.350DVCH_t^2 - 0.226DVCH_t^3 \quad (32)$$

$C(1)$ is the adjustment coefficient for the VECM. The *p*-value of $C(1)$ shows that it is significant at a 5% level in Table 5.12 and is negative as was calculated in section 5.5.2. This validates a long run cointegrating relationship between HC and CCI. $C(2)$, $C(3)$, $C(4)$ and $C(5)$ are the coefficients of the short run variables. The null hypothesis of the Wald test is such that $C(2) = C(3) = C(4) = C(5) = 0$. The F-statistic from the Wald test is 6.655985 with a *p*-value of 0.0001. Therefore, a short run relationship does exist between CCI and HC at a 5% level as the null hypothesis is rejected. The coefficients of the variables to handle for breakpoints ($C(6)$ and $C(8)$) are not significant at a 5% level and this indicates that these breakpoints have limited impact on the model. Breakpoint coefficient $C(7)$ is significant at a 5% level. This VECM model has an $R^2 = 30.36\%$ which is low and indicates that the model only explains for 30.36% of the variability in CCI. The DW statistic is 2.022502. The $DW > R^2$ which indicates the results are not spurious.

The Jarque-Bera statistic is 1.252893 with a *p*-value of 0.534488 which is an indication that the residuals follow a normal distribution. The null hypothesis of the residuals having no autocorrelation cannot be rejected as the F-statistic for the Breusch-Godfrey test is 0.793297 with a *p*-value of 0.4546.

In summary, the model assists in predicting 30.36% of CCI, HC seems to assist in the prediction of CCI in the long and short run. The low predictive power of the model indicates that other variables may exist which may assist in predicting CCI. The model is adequate as the residuals have a normal distribution and were not autocorrelated. This outcome further supports the finding of the cointegration tests which found that the model will adjust itself in the next lag. These results also support the observations in Figure 5.1 where changes HC did seem to result in changes in CCI.

5.6.3 Capital Formation predicted by Business Confidence VECM

The $VECM$ is specified with CF as the dependent variable, BCI as the predictor variable and the exogenous variables $DVBC_t^1$, $DVBC_t^2$ and $DVBC_t^3$, and with no intercepts and trends. The lag length of 1 which was determined earlier in Table 5.4 will be applied. The coefficient of BCI in the time series model to predict CF in the long run was calculated in section 5.5.3. The VECM will therefore take the following form:

$$\Delta\widehat{CF} = C(1) * (CF_{t-1} - 366.345BCI_{t-1}) + C(2) * \Delta CF_{t-1} + C(3) * \Delta BCI_{t-1} + C(4) * DVBC_t^1 + C(5) * DVBC_t^2 + C(6) * DVBC_t^3 \quad (33)$$

Table 5.13: VECM Coefficients: CF predicted by BCI

Coefficient	Value	SE	*t*-Statistic	*p*-value
$C(1)$	-0.063594	0.015134	-4.201992	0.0000
$C(2)$	-0.116626	0.081855	-1.424795	0.1566
$C(3)$	10.54052	12.47796	0.844731	0.3998
$C(4)$	339.1616	186.8694	1.814966	0.0718
$C(5)$	613.9429	248.4348	2.471243	0.0147
$C(6)$	347.5373	233.4755	1.488539	0.1390

Substituting the coefficients in Table 5.13 into the VECM in equation (12) yields:

$$\Delta\widehat{CF} = -0.064(CF_{\ t-1} - 366.345BCI_{t-1}) - 0.117\Delta CF_{t-1} + 10.54\Delta BCI_{t-1} + 339.162DVBC_t^1 + 613.943DVBC_t^2 + 347.537\ DVBC_t^3 \quad (34)$$

$C(1)$ is the adjustment coefficient for the VECM. The *p*-value of $C(1)$ show that it is significant in Table 5.13 and is negative as was calculated in section 5.5.3. This validates a long run cointegrating relationship between BCI and CF. $C(2)$ and $C(3)$ are the coefficients of the short run variables. The null hypothesis of the Wald test is such that $C(2) = C(3) = 0$. The F-statistic from the Wald test is 1.520638 with a *p*-value of 0.2224. Therefore, there is no short run relationship between BCI and CF as the null hypothesis cannot be rejected. The coefficients of the variables to handle for breakpoints ($C(4)$ and $C(6)$) are not significant at a 5% level and this indicates that these breakpoints have limited impact on the model. Breakpoint coefficient $C(5)$ is significant at a 5% level. This VECM model has an $R^2 = 16.77\%$ which is low and indicates that the model only explains 16.77% of the variability in CF. The DW statistic is 2.098617. The $DW > R^2$ which indicates the results are not spurious.

The Jarque-Bera statistic is 28.62410 with a p-value of 0.000001 which is an indication that the residuals are not normally distributed which is an indication that the model predictive results may inaccurate. The null hypothesis of the residuals having no autocorrelation is rejected as the F-statistic for the Breusch-Godfrey test is 11.77043 with a p-value of 0.0008.

In summary, this model assists in predicting 16.77% of CF. The low predictive power of the model indicates that other variables may exist which may assist in predicting CF. BCI does seem to assist in the prediction of CF in the long run but does not seem to assist in prediction in the short run. The residual diagnostic tests showed that the residuals were not normally distributed which is an indication the model needs to be re-specified by including other variables before running further analysis. These results are supported by Figure 5.2 which did show periods where both series had no co-movements.

5.6.4 Business Confidence predicted by Capital Formation VECM

The $VECM$ is specified with BCI as the dependent variable, CF as the predictor variable and the exogenous variables $DVCF_t^1$, $DVCF_t^2$, $DVCF_t^3$ and $DVCF_t^4$, and with no intercepts and trends. The lag length of 1 which was determined earlier in Table 5.4 will be applied. The coefficient of CF in the time series model to predict BCI in the long run was calculated in section 5.5.4. The VECM will therefore take the following form:

$$\widehat{\Delta BCI} = C(1) * (BCI_{t-1} - 0.002CF_{t-1}) + C(2) * \Delta BCI_{t-1} + C(3) * \Delta CF_{t-1} + C(4) * DVCF_t^1 + C(5) * DVCF_t^2 + C(6) * DVCF_t^3 + C(7) * DVCF_t^4 \quad (35)$$

Table 5.14: VECM Coefficients: BCI predicted by CF

Coefficient	Value	SE	*t*-Statistic	*p*-value
$C(1)$	-0.178828	0.050991	-3.507051	0.0006
$C(2)$	0.068315	0.087579	0.780044	0.4368
$C(3)$	0.000783	0.000589	1.330148	0.1858
$C(4)$	3.537268	1.553037	2.277645	0.0244
$C(5)$	-0.470362	1.637542	-0.287237	0.7744
$C(6)$	5.526409	2.025938	2.727828	0.0073
$C(7)$	-1.679646	1.276106	-1.316227	0.1904
$C(8)$	-0.226195	1.480250	-0.152809	0.8788

Substituting the coefficients in Table 5.14 into the VECM in equation (13) yields:

$$\widehat{\Delta BCI} = -0.179(BCI_{t-1} - 0.002CF_{t-1}) + 0.068\Delta BCI_{t-1} + 0.001\Delta CF_{t-1} + 3.537DVCF_t^1 - 0.470DVCF_t^2 + 5.526DVCF_t^3 - 1.680DVCF_t^4 \quad (36)$$

$C(1)$ is the adjustment coefficient for the VECM. The *p*-value of $C(1)$ show that it is significant in Table 5.14 and is negative as was calculated in section 5.5.4. This validates a long run cointegrating relationship between CF and BCI. $C(2)$ and $C(3)$ are the coefficients of the short run variables. The null hypothesis of the Wald test is such that $C(2) = C(3) = 0$. The F-statistic from the Wald test is 1.082838 with a *p*-value of 0.3416. Therefore, there is no short run relationship between CF and BCI as the null hypothesis cannot be rejected. The coefficients of the variables to handle for breakpoints ($C(5)$, $C(7)$ and $C(8)$) are not significant at a 5% level and this indicates that these breakpoints have limited impact on the model. Breakpoint coefficient $C(6)$ is significant at a 5% level. This VECM model has an $R^2 = 10.12\%$ which is low and indicates that the model only explains for 10.12% of the variability in BCI. The DW statistic is 2.057599. The $DW > R^2$ which indicates the results are not spurious.

The Jarque-Bera statistic is 0.636118 with a *p*-value of 0.727560 which is an indication that the residuals have a normal distribution. The null hypothesis of the residuals having no autocorrelation cannot be rejected as the F-statistic for the Breusch-Godfrey test is 1.750112 with a *p*-value of 0.1882.

In summary, this model assists in predicting 10.12% of BCI. The low predictive power of the model indicates that other variables may exist which may assist in predicting BCI. CF does seem to assist in the prediction of BCI in the long run but does not seem to assist in prediction in the short run. As was summarised in section 5.6.3, these results support the observations in Figure 5.2.

5.6.5 Business Confidence predicted by Consumer Confidence VECM

The $VECM$ is specified with BCI as the dependent variable, CCI as the predictor variable and the exogenous variables $DVCB_t^1$, $DVCB_t^2$ and $DVCB_t^3$, and with no intercepts and trends. The lag length of 2 which was determined earlier in Table 5.4 will be applied. The coefficient of CCI in the time series model to predict BCI in the long run was calculated in section 5.5.5. The VECM will therefore take the following form:

$$\widehat{\Delta BCI} = C(1) * (BCI_{t-1} + 9.449CCI_{t-1}) + C(2) * \Delta BCI_{t-1} + C(3) * \Delta BCI_{t-2} + C(4) * \Delta CCI_{t-1} + C(5) * \Delta CCI_{t-2} + C(6) * DVCB_t^1 + C(7) * DVCB_t^2 + C(8) * DVCB_t^3 \quad (37)$$

Table 5.15: VECM Coefficients: BCI predicted by CCI

Coefficient	Value	SE	*t*-Statistic	*p*-value
$C(1)$	-0.020325	0.005879	-3.457381	0.0007
$C(2)$	-0.154087	0.081571	-1.888993	0.0611
$C(3)$	0.160425	0.080303	1.997742	0.0478
$C(4)$	0.461834	0.092998	4.966050	0.0000
$C(5)$	0.351354	0.090248	3.893197	0.0002
$C(6)$	1.032862	1.071358	0.964069	0.3368
$C(7)$	3.373156	1.612853	2.091422	0.0385
$C(8)$	0.880293	1.181924	0.744797	0.4577

Substituting the coefficients in Table 5.15 into the VECM in equation (14) yields:

$$\widehat{\Delta BCI} = -0.020(BCI_{t-1} + 9.449CCI_{t-1}) - 0.154\Delta BCI_{t-1} + 0.160\Delta BCI_{t-2} + 0.462\Delta CCI_{t-1} + 0.351\Delta CCI_{t-2} + 1.033DVCB_t^1 + 3.373DVCB_t^2 + 0.880DVCB_t^3 \quad (38)$$

$C(1)$ is the adjustment coefficient for the VECM. The *p*-value of $C(1)$ show that it is significant in Table 5.15 and is negative as was calculated in section 5.5.5. This validates a long run cointegrating relationship between CCI and BCI. $C(2)$, $C(3)$, $C(4)$ and $C(5)$ are the coefficients of the short run variables. The null hypothesis of the Wald test is such that $C(2) = C(3) = C(4) = C(5) = 0$. The F-statistic from the Wald test is 9.763827 with a *p*-value of 0.0000. Therefore, there is a short run relationship between CCI and BCI as the null hypothesis is rejected. The coefficients of the variables to handle for breakpoints ($C(6)$ and $C(8)$) are not significant at a 5% level and this indicates that these breakpoints have limited impact on the model. Breakpoint coefficient $C(7)$ is significant at a 5% level. This VECM model has an $R^2 = 24.35\%$ which is low and indicates that the model only explains 24.35% of the variability in BCI. The DW statistic is 2.065577. The $DW > R^2$ which indicates the results are not spurious.

The Jarque-Bera statistic is 0.824646 with a *p*-value of 0.662110 which is an indication that the residuals follow a normal distribution. The null hypothesis of the residuals having no autocorrelation cannot be rejected as the F-statistic for the Breusch-Godfrey test is 2.674902 with a *p*-value of 0.0728.

In summary, this model assists in predicting 24.35% of BCI. The low predictive power of the model indicates that other variables may exist which may assist in predicting BCI. CCI does seem to assist in the prediction of BCI in the short and long run. The model is stable as the residuals have a normal distribution and are not autocorrelated. These results support the observations in Figure 5.3 where there appeared to be co-movement between the variables.

5.6.6 Consumer Confidence predicted by Business Confidence Index VECM

The $VECM$ is specified with CCI as the dependent variable), BCI as the predictor variable and the exogenous variables $DVBCC_t^1$, $DVBCC_t^2$, $DVBCC_t^3$, $DVBCC_t^4$ and $DVBCC_t^5$, and with no intercepts and trends. The lag length of 1 which was determined earlier in Table 5.4 will be applied. The coefficient of BCI in the time series model to predict CCI in the long run was calculated in section 5.5.6. The VECM will therefore take the following form:

$$\widehat{\Delta CCI} = C(1) * (CCI_{t-1} - 0.0695BCI_{t-1}) + C(2) * \Delta CCI_{t-1} + C(3) * \Delta BCI_{t-1} + C(4) * DVBCC_t^1 + C(5) * DVBCC_t^2 + C(6) * DVBCC_t^3 + C(7) * DVBCC_t^4 + C(8) * DVBCC_t^5 \quad (39)$$

Table 5.16: VECM Coefficients: CCI predicted by BCI

Coefficient	Value	SE	*t*-Statistic	*p*-value
$C(1)$	-0.337380	0.074447	-4.531822	0.0000
$C(2)$	-0.247976	0.081183	-3.054548	0.0027
$C(3)$	0.288091	0.074317	3.876495	0.0002
$C(4)$	-1.256689	1.345732	-0.933833	0.3521
$C(5)$	1.502599	1.520050	0.988520	0.3247
$C(6)$	-2.160946	1.574387	-1.372564	0.1723
$C(7)$	3.122701	1.412758	2.210359	0.0288
$C(8)$	-3.062232	1.534297	-1.995853	0.0480

Substituting the coefficients in Table 5.16 into the VECM in equation (15) yields:

$$\widehat{\Delta CCI} = -0.337(CCI_{t-1} - 0.0695BCI_{t-1}) - 0.248\Delta CCI_{t-1} + 0.288\Delta BCI_{t-1} - 1.257DVBCC_t^1 + 1.503DVBCC_t^2 - 2.161DVBCC_t^3 + 3.123DVBCC_t^4 - 3.062DVBCC_t^5 \quad (40)$$

$C(1)$ is the adjustment coefficient for the VECM. The *p*-value of $C(1)$ is significant in Table 5.16 and is negative as was calculated in section 5.5.6. This validates a long run cointegrating relationship between BCI and CCI. $C(2)$ and $C(3)$ are the coefficients of the short run variables. The null hypothesis of the Wald test is such that $C(2) = C(3) = 0$. The F-statistic from the Wald test is 11.81631 with a *p*-value of 0.0000. Therefore, there is a short run relationship between BCI and CCI as the null hypothesis is rejected. The coefficients of the variables to handle for breakpoints ($C(4)$, $C(5)$ and $C(6)$) are not significant at a 5% level and this indicates that these breakpoints have limited impact on the model. Breakpoint coefficients ($C(7)$ and $C(8)$) is significant at a 5% level. This VECM model has an $R^2 = 33.44\%$ which is low and indicates that the model only explains 33.44% of the variability in CCI. The DW statistic is 2.172333. The $DW > R^2$ which indicates the results are not spurious.

The Jarque-Bera statistic is 4.738552 with a *p*-value of 0.093548 which is an indication that the residuals follow a normal distribution. The null hypothesis of the residuals having no autocorrelation cannot be rejected as the F-statistic for the Breusch-Godfrey test is 1.305596 with a *p*-value of 0.2553.

In summary, this model assists in predicting 33.44% of CCI. The low predictive power of the model indicates that other variables may exist which may assist in predicting CCI. BCI does seem to assist in the prediction of CCI in the short and long run. These results are similar to section 5.6.5 and support the co-movement observed in Figure 5.3. The residual diagnostic tests show that the model is adequate.

The next section provides the results of the Granger causality tests between the pairs of variables. These results will determine if the co-movement of variables observed in section 5.6 is due to Granger causal relationships between the variables.

5.7 Granger Causality

The results from the Granger causality test for the pairs of variables being considered in this research report are given in Table 5.17. These results were obtained after incorporating the exogenous variables which were determined in section 5.2. The null hypothesis being tested is that of one variable not Granger causing the other variable.

Table 5.17 Granger causality Results

Null Hypothesis	Chi-sq Statistic	P-value	Decision	Type for Causality
$\Delta CCI \nearrow \Delta HC$	0.166170	0.9203	Do not reject H_0	No causality
$\Delta HC \nearrow \Delta CCI$	12.54073	0.0019	Reject H_0	Uni-directional causality
$\Delta BCI \nearrow \Delta CF$	0.713571	0.3983	Do not reject H_0	No causality
$\Delta CF \nearrow \Delta BCI$	1.769292	0.1835	Do not reject H_0	No causality
$\Delta CCI \nearrow \Delta BCI$	27.19170	0.0000	Reject H_0	Bi-directional causality
$\Delta BCI \nearrow \Delta CCI$	15.02721	0.0001	Reject H_0	Bi-directional causality

Notation: $\nearrow$ does not Granger cause.

Granger causality results in Table 5.17 supports some of the observations made in the plots of the data in section 5.1, the results of the cointegration tests in Section 5.5 and the VECM results in Section 5.6. The result that ΔCCI does not Granger cause ΔHC is consistent with the results of the VECM which showed no long run relationship between this pair of variables. Rather, it is ΔHC that Granger causes ΔCCI. This outcome is consistent with the results of the VECM which showed that ΔHC assists in the prediction of ΔCCI in the short and long run. This was also visible in Figure 5.1 where ΔHC resulted in ΔCCI for observed time periods.

There was no observable causal relationship between ΔBCI and ΔCF. This supports the observations in figure 5.2 where it was difficult to identify any variable influencing the other. These results support the cointegration tests which did not find meaningful results and showed that the variables negatively influence each other which is unlikely. The VECM analysis thereafter also showed that these variables did not contribute much in explaining the variability in each other.

The bi-directional Granger causality relationship between ΔBCI and ΔCCI is consistent with the results of the VECM in section 5.6.5 and 5.6.6 which found that these variables influence each other in the long and short run.

To gain further insight into the causal relationship between the pairs of variables, VDCs and IRFs are analysed next.

5.8 Variance Decomposition

The Variance Decomposition (VDC) indicates the amount of information each variable contributes to the other variables in the $VECM$. Below are results from the VDC for the $VECM$ models specified in section 5.6 (equations 30, 32, 38 and 40). The variance decomposition and impulse response function (section 5.9) for capital formation and business confidence specified in section 5.6 (equations 34 and 36) will not be considered as the model residuals were found to be not normally distributed and autocorrelated. These models (equations 34 and 36) may therefore result in erroneous forecasts. The first column provides the period being evaluated. The second column, is the standard error (SE) which is the forecast error of the dependent variable at the given period. The source of this forecast error is the variation in the current and future values of the shocks to each endogenous variable in the model. The last two columns indicate the percentage of the forecast variance due to each shock for each dependent variable. The impact of the shock in the short run (period 3 or less) and the long run (period 6 or larger) will be evaluated.

5.8.1 Variance Decomposition of Household Consumption predicted by Consumer Confidence

Table 5.18 shows that in the short run (period 3 for example), a shock in HC will account for a 98.6% change in HC and in contrast a shock in CCI will only result in a 1.4% change in HC. There is not much of a change in the long run (period 6 for example), where a shock in HC will account for a 96.7% change in HC and a shock in CCI will only result in a 3.27% change in HC. These results are supported by the Granger causality tests which found that ΔCCI does not Granger Cause ΔHC. Figure 5.4 is a graphical representation of the results from Table 5.18.

Table 5.18: VDC of HC for HC predicted by CCI

VDC of HC			
Period	**S.E. (R'mil)**	**HC (%)**	**CCI (%)**
1	9448.996	100.0000	0.000000
2	15994.17	99.23231	0.767685
3	22989.74	98.58004	1.419964
4	29735.60	97.85780	2.142195
5	36259.68	97.25728	2.742715
6	42492.14	96.72861	3.271386
7	48434.75	96.28588	3.714118
8	54091.20	95.90922	4.090775

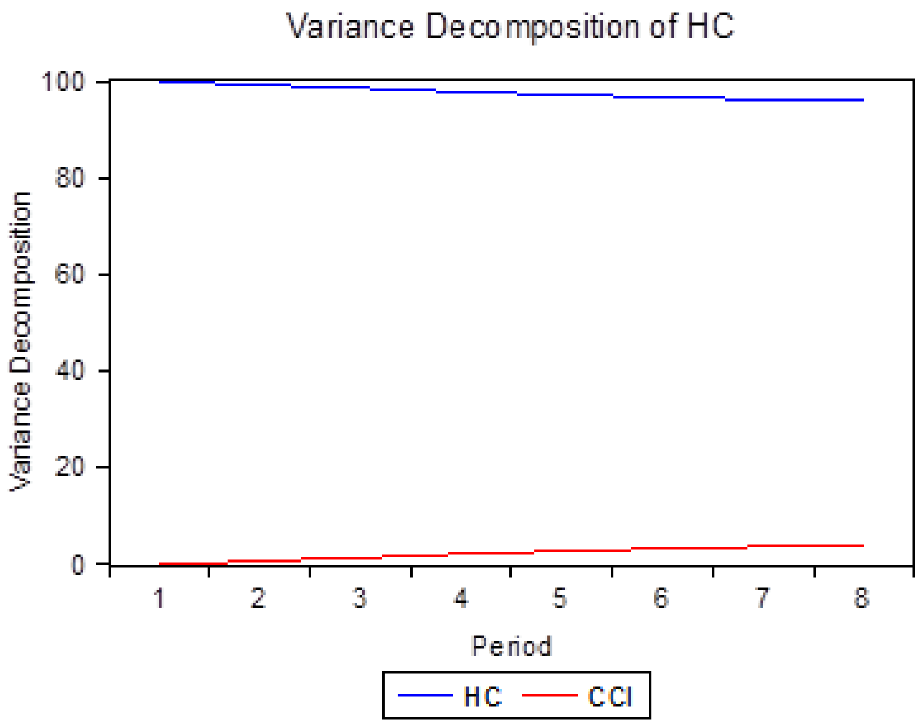

Figure 5.4: VDC: Household Consumption predicted Consumer Confidence

5.8.2 Variance Decomposition of Consumer Confidence predicted by Household Consumption

Table 5.19 shows that in the short run (period 3 for example), a shock in CCI will account for 91.9% change in CCI, and a shock in HC will only result in an 8.1% change in CCI. In the long run (period 6 for example), a shock in CCI will account for 84.6% change in CCI and a shock in HC will result in a 15.4% change in HC. The Granger causality tests which found HC to Granger cause CCI is further support by this outcome. Figure 5.5 is a graphical representation of the results from Table 5.19.

Table 5.19: VDC of CCI for CCI predicted by HC

VDC of CCI			
Period	**S.E. (Index)**	**CCI (%)**	**HC (%)**
1	6.801960	100.0000	0.000000
2	7.776636	94.22435	5.775648
3	8.839057	91.91518	8.084825
4	9.394770	88.27529	11.72471
5	9.827354	86.30685	13.69315
6	10.10680	84.61698	15.38302
7	10.30789	83.58386	16.41614
8	10.44396	82.82805	17.17195

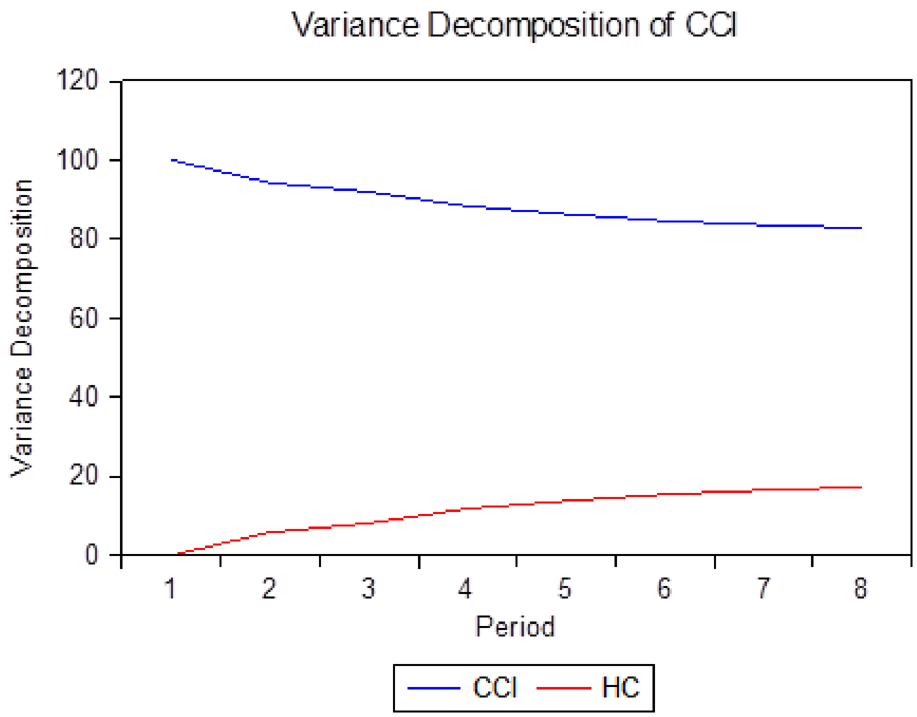

Figure 5.5: VDC: Consumer Confidence predicted Household Consumption

5.8.3 Variance Decomposition of Business Confidence predicted Consumer Confidence

Table 5.22 shows that in the short run (period 3 for example), a shock in BCI will account for a 96.1% change in BCI and a shock in CCI will only result in a 3.9% change in BCI. There is not much of a change in the long run (period 6 for example), where a shock in BCI will account for a 97% change in BCI and a shock in CCI will only result in a 3% change in BCI. These results show that previous values BCI are more likely to affect values after a shock rather than CCI. These results support the small adjustment coefficient (2%) observed in the cointegration tests (section 5.5.5). Figure 5.8 is a graphical representation of the results from Table 5.22.

Table 5.20: VDC of BCI for BCI predicted by CCI

VDC of BCI			
Period	**S.E. (Index)**	**BCI (%)**	**CCI (%)**
1	6.860992	100.0000	0.000000
2	9.295082	96.21658	3.783422
3	12.11229	96.09558	3.904421
4	13.88770	96.99375	3.006249
5	15.34273	97.51005	2.489946
6	16.48967	97.04649	2.953508
7	17.45102	95.85698	4.143024
8	18.32908	93.78355	6.216447

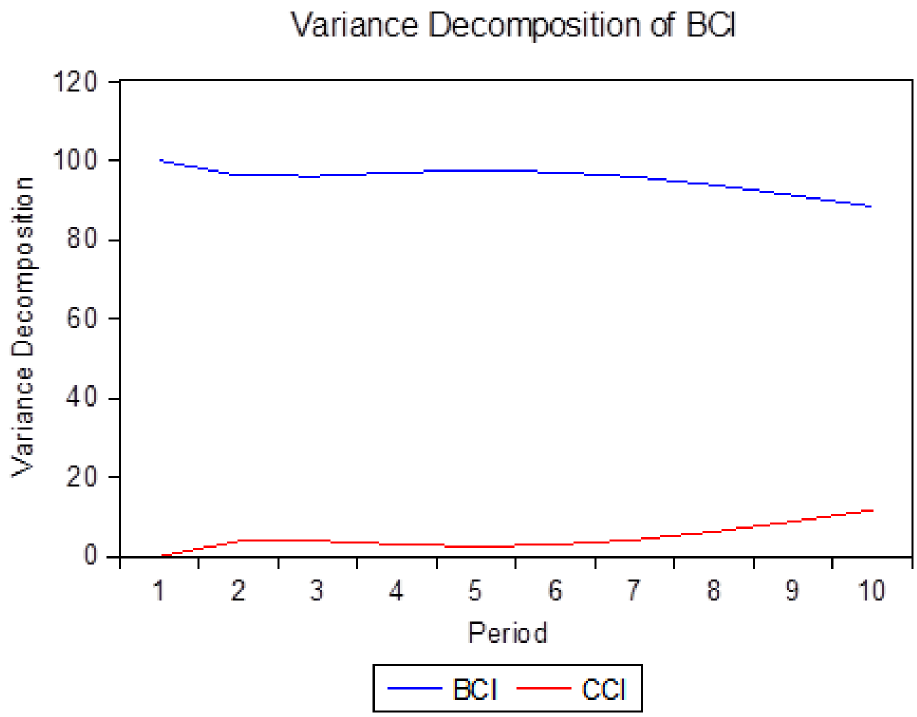

Figure 5.6: VDC: Business Confidence predicted Consumer Confidence

5.8.4 Variance Decomposition of Consumer Confidence predicted by Business Confidence

In the short run (period 3 for example), a shock in CCI will account for a 91.8% change in CCI, while a shock in BCI will result in 8.1% change in CCI. There is not much of a change in the long run (period 6 for example), where a shock in CCI will account for 89.3% change in CCI and a shock in BCI will only result in a 10.7% change in CCI. These results show that previous values CCI are more likely to affect values after a shock rather than BCI. A shock of BCI on CCI has minimal or marginal increases after 1 lag. Figure 5.9 is a graphical representation of the results from Table 5.23.

Table 5.21: VDC of CCI for CCI predicted by BCI

VDC of CCI			
Period	**S.E. (Index)**	**CCI (%)**	**BCI (%)**
1	6.630205	100.0000	0.000000
2	7.736502	91.53449	8.465510
3	8.551388	91.83631	8.163690
4	8.876370	90.28760	9.712401
5	9.085312	89.92457	10.07543
6	9.193836	89.30145	10.69855
7	9.263390	88.93427	11.06573
8	9.307678	88.54588	11.45412

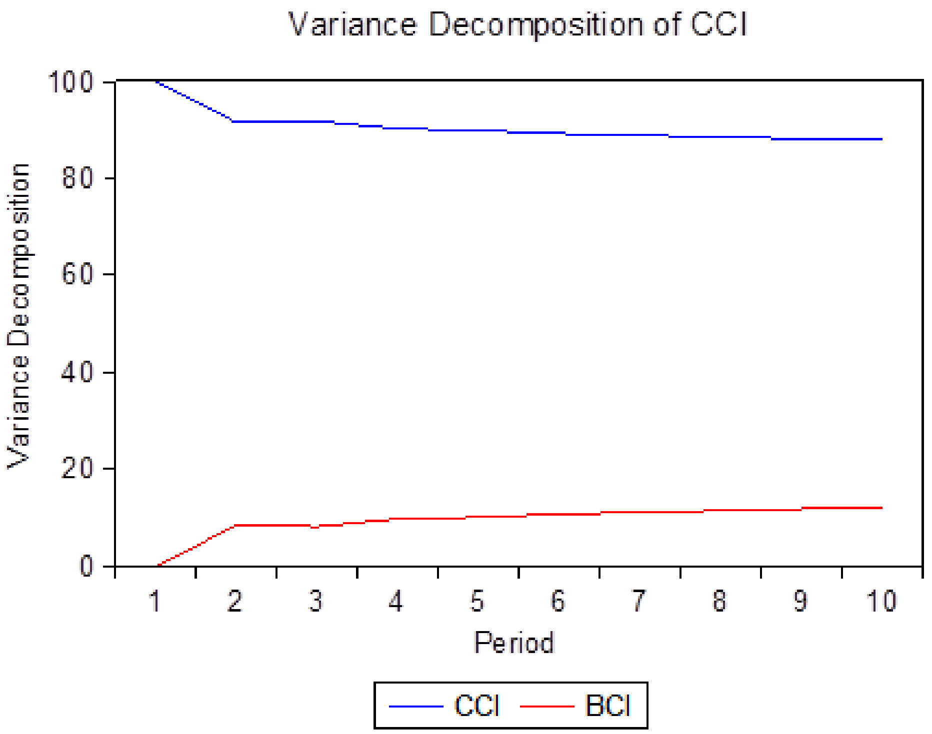

Figure 5.7: VDC: Consumer Confidence predicted Business Confidence

5.9 Impulse Response Function

The impulse response function analyses the responsiveness of the dependent variables in the $VECM$, specified in section 5.6 (equations 30, 32, 38 and 40), when a dependent variable in the model receives an impulse.

5.9.1 Impulse Response Function of Household Consumption predicted by Consumer Confidence

Consider the VECM specified in (30) where ϵ_t is the error term:

$$\Delta HC = 0.001(HC_{t-1} + 111286.638CCI_{t-1}) + 0.321\Delta HC_{t-1} + 0.204\Delta HC_{t-2} + 50.057\Delta CCI_{t-1} + 36.069\Delta CCI_{t-2} + 760.776DVCC_t^1 + 2487.678DVCC_t^2 + 1688.478DVCC_t^3 + 2629.856DVCC_t^4 + \epsilon_t$$

Table 5.24 shows the impulse response of HC to impulses in HC and CCI. When the impulse is in HC, the response of HC at each response period is large and positive. When the impulse is in CCI, the response of HC at each response period is positive but smaller than the impulses caused by HC. These results show that previous values HC are more likely to affect values after a shock. In order to display the response function clearer, a graphical representation is provided in Figure 5.10.

Table 5.22: IRF of HC for HC predicted by CCI

Response of HC		
Period	**HC (R'mil)**	**CCI (R'mil)**
1	9448.996	0.000000
2	12828.33	1401.371
3	16345.45	2353.948
4	18553.73	3381.789
5	20333.21	4137.490
6	21628.93	4796.596
7	22633.61	5297.439
8	23395.99	5706.123

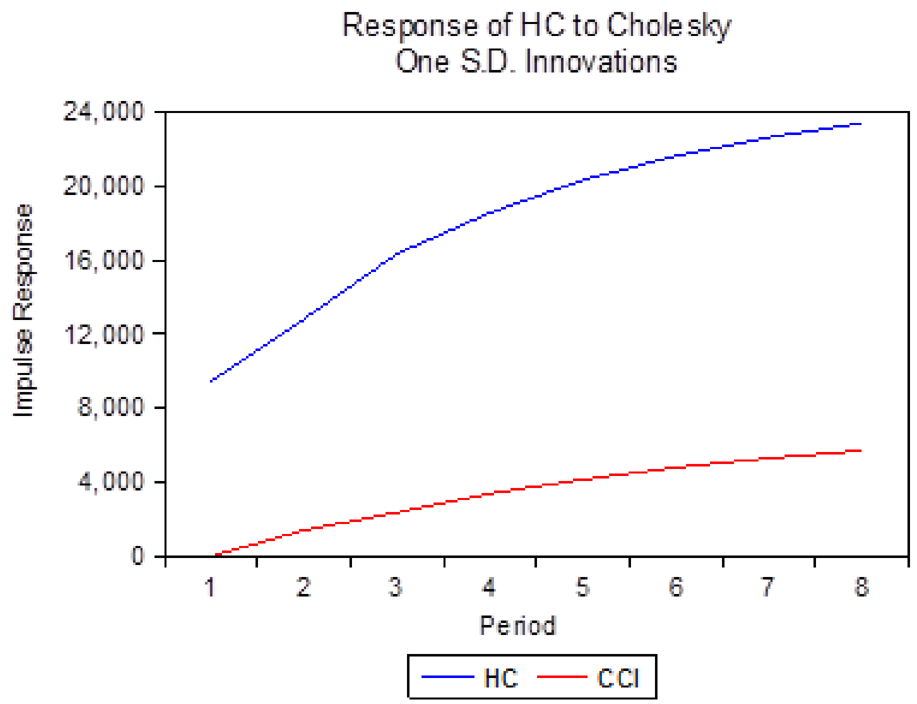

Figure 5.8: IRF: Household Consumption predicted Consumer Consumption

5.9.2 Impulse Response Function of Consumer Confidence predicted by Household Consumption

Consider the VECM specified in (32) where ϵ_t is the error term:

$$\Delta CCI = -0.379(CCI_{t-1} + 0.000005 * HC_{t-1}) - 0.21 * \Delta CCI_{t-1} + 0.079\Delta CCI_{t-2} + 0.0002\Delta HC_{t-1} + 0.00003\Delta HC_{t-2} - 1.061 DVCH_t^1 + 4.350 DVCH_t^2 - 0.226 DVCH_t^3 + \epsilon_t$$

Table 5.25 shows the impulse response of CCI to impulses in CCI and HC. When the impulse is in CCI, the response of CCI is positive across the response periods with fluctuations. The highest effect is in the first period and lowest effect in period eight. When the impulse is in HC, the response of CCI is zero in the first response period. This is followed by smaller positive values over the remaining response periods as compared to impulses in CCI. The low CCI impulse responses for impulses in CCI and HC is an indication that CCI cannot be shocked into increasing and may be largely dependent on the perception of people which takes time to change. The response function is graphically represented in Figure 5.11.

Table 5.23: IRF of CCI for CCI predicted by HC

Response of CCI		
Period	**CCI (Index)**	**HC (Index)**
1	6.801960	0.000000
2	3.273609	1.868926
3	3.850864	1.680387
4	2.470010	2.007944
5	2.332208	1.695874
6	1.755434	1.577638
7	1.541403	1.314992
8	1.239319	1.134892

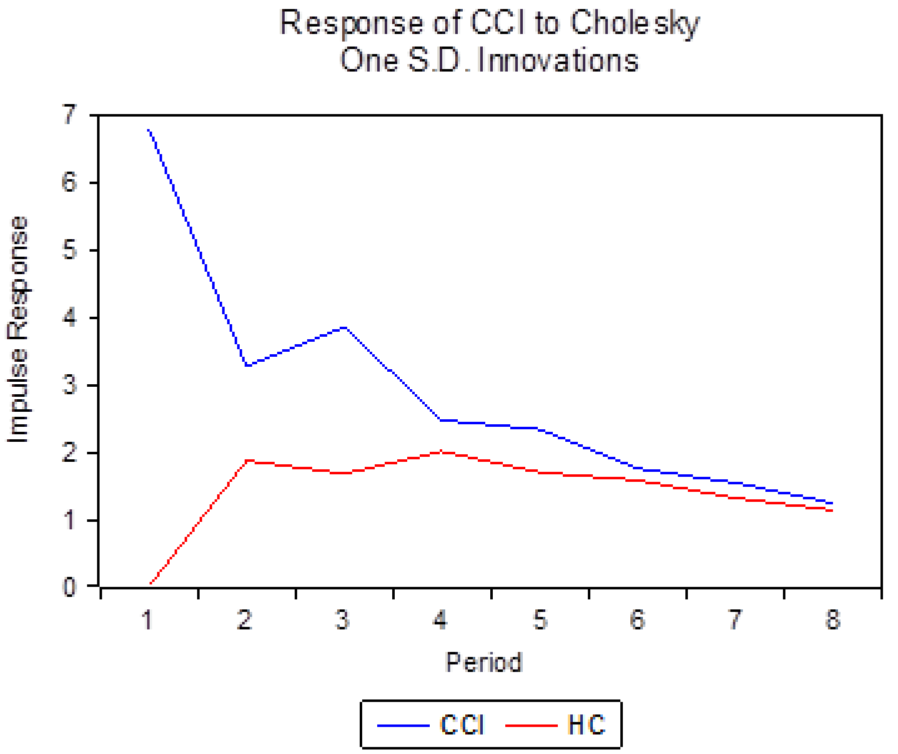

Figure 5.9: IRF: Household Consumption predicted Consumer Consumption

5.9.3 Impulse Response Function of Business Confidence predicted by Consumer Confidence

Consider the VECM specified in (38) where ϵ_t is the error term:

$$D(BCI) = -0.020(BCI_{t-1} + 9.449CCI_{t-1}) - 0.154\Delta BCI_{t-1} + 0.160\Delta BCI_{t-2} + 0.462\Delta CCI_{t-1} + 0.351\Delta CCI_{t-2} + 1.033DVCB_t^1 + 3.373DVCB_t^2 + 0.880DVCB_t^3 + \epsilon_t$$

Table 5.28 shows the impulse response of BCI to impulses in BCI and CCI. When the impulse is in BCI, the response of BCI is positive across eight response periods with fluctuations. The highest effect is in the third period and lowest effect in period eight. When the impulse is in CCI the response of BCI is zero in the first response period and positive for the next three periods. Negative effects are observed thereafter. The response function is graphically represented in Figure 5.14.

Table 5.24: IRF of BCI for BCI predicted by CCI

Response of BCI		
Period	**BCI (Index)**	**CCI (Index)**
1	6.860992	0.000000
2	6.004707	1.807988
3	7.605907	1.568204
4	6.789000	0.264600
5	6.516755	-0.251442
6	5.860054	-1.472936
7	5.295540	-2.141549
8	4.811405	-2.875306

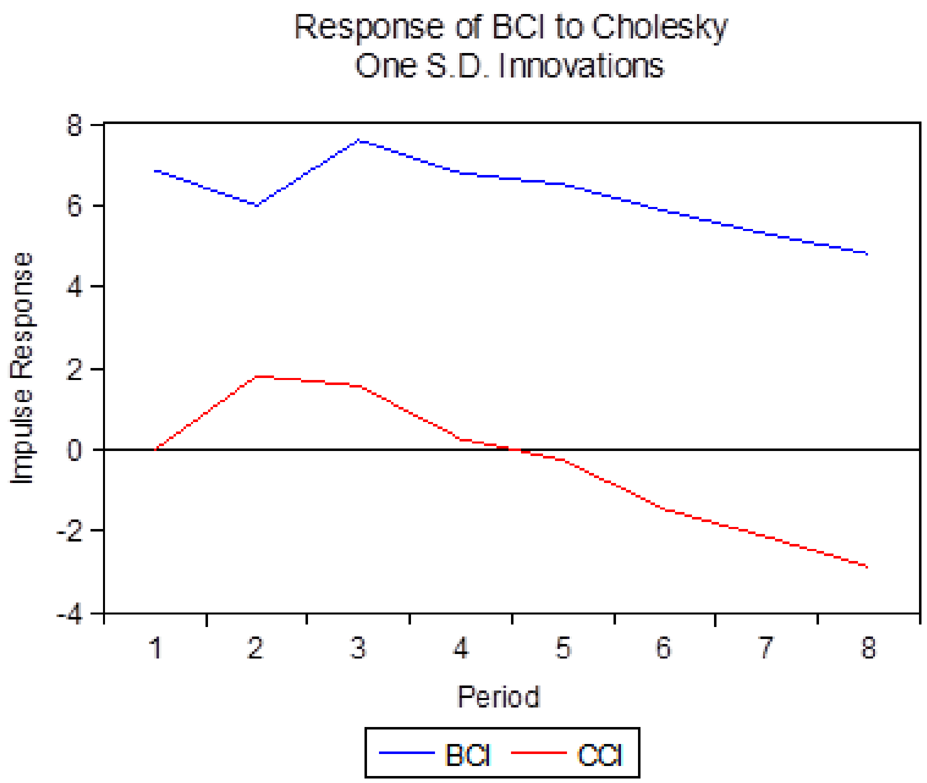

Figure 5.10: IRF: Business Confidence predicted Consumer Confidence

5.9.4 Impulse Response Function of Consumer Confidence predicted by Business Confidence

Consider the VECM specified in (40) where ϵ_t is the error term:

$$D(CCI) = -0.337(\,CCI_{t-1} - 0.0695BCI_{t-1}) - 0.248\Delta CCI_{t-1} + 0.288\Delta BCI_{t-1} - 1.257DVBCC_t^1 + 1.503DVBCC_t^2 - 2.161DVBCC_t^3 + 3.123DVBCC_t^4 - 3.062DVBCC_t^5 + \epsilon_t$$

Table 5.29 shows the impulse response of CCI to impulses in CCI and BCI. When the impulse is in CCI, the response of CCI is positive across the response periods with fluctuations. The highest effect is in the first period and lowest effect in period eight. When the impulse is in CCI the response of

BCI is zero in the first response period and positive for the rest of the periods. Both effects have similar values in period eight. The response function is graphically represented in Figure 5.15.

Table 5.25: IRF of CCI for CCI predicted by BCI

Response of CCI		
Period	**CCI (Index)**	**BCI (Index)**
1	6.630205	0.000000
2	3.290431	2.250978
3	3.517084	0.950210
4	1.995272	1.297149
5	1.757498	0.814956
6	1.121228	0.852391
7	0.911787	0.672628
8	0.628479	0.653826

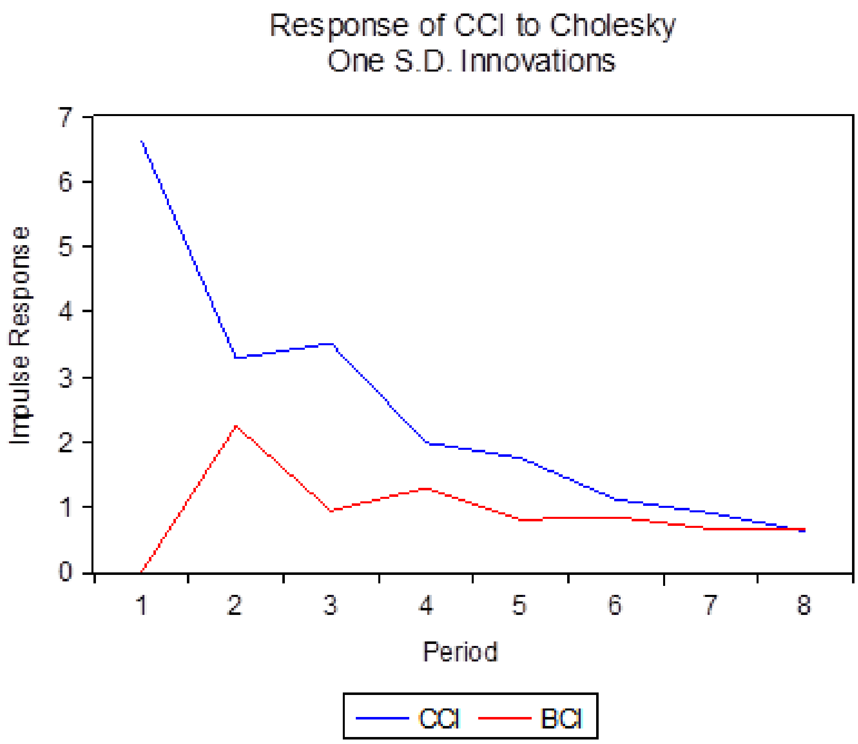

Figure 5.11: IRF: Consumer Confidence predicted Business Confidence

Chapter 6: Conclusion

6.1 Summary

This research report explored the Granger causality relationship between confidence and consumption using South Africa data between June 1982 and March 2017. The plots of data did show periods where the pairs of variables considered moved together but, also showed periods where there were large swings in the data. These large swings were an indication of structural breaks due to changes in the political and economic nature of the country as evidence of the tests carried out. The structural breaks were included as exogenous variables in the models to ensure the model results were not biased or suffered from model misspecification. The variables were tested for stationarity and the number of times they must be differenced before they become stationary was determined. The lag length for each of the pairs of variables considered was calculated and a decision of the lag length was based on the SBC information criteria. The Johansen procedure was used thereafter to determine if the variables had a cointegrating relationship. VECMs determined the short and long run dynamics of the variable pairs. Finally, the causal relationship between the variables was further explored using decomposition functions, which determine the amount each variable contributes to each other, and the IRFs, which assess the impact on the dependent variable given a shock to the system.

6.2 Conclusions and recommendations

Figure 5.1 did show periods were a change in household consumption resulted in changes in consumer confidence. The AIC and SBC information criteria results showed that the variables impacted each other up to two lags. These variables were found to be integrated of the same order and therefore cointegration analysis was performed. A cointegration relationship did exist for CCI predicting HC and HC predicting CCI. The VECM results for CCI predicting HC found no converging long run relationship between these variables but did find a short run relationship. The residual diagnostics for CCI predicting HC found that the residuals were not normally distributed and autocorrelated which indicates that other variables may need to be included to improve model specification. The VECM results for HC predicting CCI, found a long and short run relationship between these variables. No issues could be identified with the residual diagnostics for HC predicting CCI. The Granger causality results confirm these observations by only finding that HC Granger causes CCI. The VDC found that a shock to CCI in the long and short run will account for the largest percentage change on CCI. HC will account for a larger percentage of the change in CCI

in the long run. The IRF showed that impulses to CCI and HC do not result in a significant response in CCI for the response period.

Figure 5.2 did show periods of large swings in one variable which did not correspond to the changes in the other variable. The information criteria results showed that the variables impacted each other up to one lag. These variables were found to be integrated by the same order and therefore cointegration analysis was performed. The VECM analysis found no relationship in the short run between the variable pairs however one in the long run did exist. The residual diagnostics showed that both these models were not normally distributed. The results from both these models indicate that additional variables may need to be included to improve the model specification.

Figure 5.3 did show periods of large swings in one variable which did not correspond with the changes in the other variable, but overall both variables seemed to move close together. The information criteria results showed that for CCI predicting BCI, the variables impact each other for up to two lags, while for BCI predicting CCI the variables impacted each other for up to one lag. These variables were found to be integrated by the same order and therefore cointegration analysis was performed. The diagnostic tests found the residuals to be normally distributed and not autocorrelated for of both VECM models. The Granger causality tests found bi-direction Granger causality between the variables. The VDC found that a shock to BCI in the long and short run will account for the largest percentage change on BCI. The IRF showed that impulses to BCI remain positive over the response period while CCI results in negative responses from lag period 5. The VDC found that a shock to CCI in the long and short run will account for the largest percentage change on CCI. BCI will account for a consistent percentage after the first lag when predicting CCI. The IRF showed that impulses to CCI are significant in the first lag period and while BCI only moves from zero in the second lag period when predicting CCI.

In summary, the three Granger causality relationships were observed in this research report. That is, HC Granger causes CCI, CCI Granger causes BCI and BCI Granger causes CCI. These results seem plausible. As households consume more, there would be an expectation that the confidence of consumers increases. As business confidence increases, consumers become more optimistic about the future of the country and their confidence increases. The opposite also holds true. As consumer confidence increases, business become more optimistic about expansion of the country and their confidence increases. The rest of the relationships explored may require additional variables to improve model specification. In order to model consumers, variables like income, interest rates, inflation and consumer price index (CPI) may need to be considered. A model for businesses may need to similarly include inflation, GDP, interest rates, average employee salaries, CPI and Trade volume statistics. These variables may also improve the model fit of the VECM models defined in this report.

Appendix

Appendix A: Data Description

a) Consumption

GDP is one of the primary indicators of a country's economic performance. There are three ways in which it can be measured - by the value of production, by the total income generated or by the value of expenditure on goods and services produced. The last measure is an indication of the consumption in the economy and is called the expenditure-based gross domestic product GDP(E). The Household final consumption expenditure (HFCE) is the largest part of the GDP(E) and is a representation of consumer consumption which is used in this research report.

The HFCE consists of the market value of all tangible and intangible goods and services purchased anywhere in the world by households. It excludes purchases of residences but includes the opportunity cost of not renting the residence. Costs incurred to obtain permits and licenses from government is included. The total expenditure of all households in the economy on consumer goods and services is called total or aggregate consumption expenditure, or simply total consumption. Consumption expenditure by households is the largest component of expenditure in South Africa and include both spending on domestic goods and foreign goods. It is usually between 60% to 63% of total expenditure in the economy and is therefore significantly influences GDP. HFCE is based on local currency.

Most of the source data used in the compilation of the HFCE originates from statistical surveys conducted by Statistics SA. The Retail Trade Sales (RTS), Motor Trade Sales (MTS) surveys, the Quarterly Financial Statements (QFS) surveys of the formal business sector, the QFS survey of municipalities, and the Large Sample Survey (LSS) of the retail trade industry are included in the data source (Statistics South Africa).

Gross fixed capital formation (GFCF) by private enterprises is a component of GDP that groups transactions on the net acquisitions of capital assets, both existing and new. This is an indication of consumption behaviour of businesses to keep operating and is referred to as capital formation (CF) in this research report.

The compilation of GFCF estimates is based on official data which is compiled and published by Stats SA, and data produced by other government organisations and compiled as part of those organisations’ administrative duties, e.g. building plans passed and completed. Data compiled by the SARB for national accounting purposes replaces data from Statistics South Africa as the data becomes available (*Statistics South Africa*).

b) Confidence Index

The quarterly FNB/BER Consumer Confidence Index (*CCI*) and Business Confidence Index (*BCI*), published by BER, will be used as measures of confidence for consumers and businesses, respectively. The CCI is an assessment of individuals expected attitudes and expectations of the economy, the expected financial position of households and the rating of the appropriateness to buy durable goods (such as furniture, appliances and electronic equipment). The FNB/BER CCI is measured on a scale between –100 (lack of confidence) and 100 (extreme confidence). The BCI is an assessment of the level of optimism that senior executives in the companies have about current and expected developments regarding sales, orders, employment, inventories and selling prices. The index is measured on a scale of 0 (lack of confidence) to 100 (extreme confidence) (*Kershoff, 2000).*

Appendix B: Stability tests

Below are the results of running the least squares with breakpoints. The method used was Bai-Perron tests of L+1 breaks vs. L sequential determined breaks. Error distributions were allowed to be different across breaks. A 5% significance level was specified.

a) Consumer Confidence predicting Household Consumption

Table A.1: Stability tests for HC predicted by CCI

Variable	Coefficient	SE	*t*-statistic	*p*-value
6/01/1982 - 3/01/1988 -- 24 obs				
CCI	767.9005	354.3489	2.167075	0.0321
C	755280.5	4964.574	152.1340	0.0000
6/01/1988 - 3/01/1995 -- 28 obs				
CCI	634.0120	4095.148	0.154820	0.8772
C	855992.3	34445.52	24.85061	0.0000
6/01/1995 - 3/01/2004 -- 36 obs				
CCI	-6170.547	4576.908	-1.348191	0.1799
C	1087612.	37424.76	29.06131	0.0000
6/01/2004 - 12/01/2009 -- 23 obs				
CCI	-3542.414	7904.970	-0.448125	0.6548
C	1532292.	119888.7	12.78096	0.0000
3/01/2010 - 3/01/2017 -- 29 obs				
CCI	-8465.945	828.5973	-10.21720	0.0000
C	1774837.	7061.277	251.3478	0.0000

Adjusted R^2	0.734702	**AIC**	27.31839
S.E. of regression	199962.3	**SBC**	27.52851
***p*-value**	0.000000	**DW statistic**	1.908504

b) Household Consumption predicting Consumer Confidence

Table A.2: Stability tests for CCI predicted by HC

Variable	Coefficient	SE	*t*-Statistic	*p*-value
6/01/1982 - 12/01/1997 -- 63 obs				
HC	6.33E-05	1.41E-05	4.483789	0.0000
C	-53.26418	11.93116	-4.464291	0.0000
3/01/1998 - 3/01/2004 -- 25 obs				
HC	-9.13E-06	1.96E-05	-0.465372	0.6424
C	7.078135	22.15950	0.319418	0.7499
6/01/2004 - 3/01/2010 -- 24 obs				
HC	-2.47E-05	1.74E-05	-1.420085	0.1579
C	48.80747	26.02249	1.875588	0.0629
6/01/2010 - 3/01/2017 -- 28 obs				
HC	-9.83E-05	1.03E-05	-9.540914	0.0000
C	174.5372	18.40510	9.483085	0.0000

Adjusted R^2	0.399175	**AIC**	7.146232
S.E. of regression	8.385088	**SBC**	7.314326
***p*-value**	0.000000	**DW statistic**	0.905916

c) Business Confidence predicting Capital Formation

Table A.3: Stability tests for CF predicted by BCI

Variable	Coefficient	SE	*t*-Statistic	*p*-value
6/01/1982 - 3/01/1996 -- 56 obs				
BCI	31.52862	9.854330	3.199469	0.0017
C	12753.29	422.4491	30.18895	0.0000
6/01/1996 - 9/01/2004 -- 34 obs				
BCI	59.72227	41.09647	1.453221	0.1485
C	14450.33	1873.479	7.713100	0.0000
12/01/2004 - 12/01/2009 -- 21 obs				
BCI	-28.84460	59.22388	-0.487043	0.6270
C	31590.11	3971.308	7.954587	0.0000
3/01/2010 - 3/01/2017 -- 29 obs				
BCI	21.20889	44.35150	0.478200	0.6333
C	22996.17	1932.225	11.90140	0.0000

Adjusted R^2	0.664140	**AIC**	19.20369
S.E. of regression	3481.382	**SBC**	19.37179
***p*-value**	0.000000	**DW statistic**	1.785476

d) Capital Formation predicting Business Confidence

Table A.4: Stability tests for BCI predicted by CF

Variable	Coefficient	SE	*t*-Statistic	*p*-value
6/01/1982 - 6/01/1987 -- 21 obs				
CF	0.000338	0.001607	0.210159	0.8339
C	23.97337	23.01244	1.041757	0.2995
9/01/1987 - 3/01/1996 -- 35 obs				
CF	0.010272	0.002080	4.938815	0.0000
C	-97.26754	28.84992	-3.371501	0.0010
6/01/1996 - 9/01/2001 -- 22 obs				
CF	0.002316	0.003236	0.715446	0.4756
C	-6.931114	52.38937	-0.132300	0.8950
12/01/2001 - 12/01/2007 -- 25 obs				
CF	0.001774	0.000544	3.258899	0.0014
C	29.71313	13.51928	2.197834	0.0297
3/01/2008 - 3/01/2017 -- 37 obs				
CF	-0.000885	0.000401	-2.205915	0.0291
C	63.40415	10.22533	6.200692	0.0000

Adjusted R^2	0.527789	**AIC**	8.115750
S.E. of regression	13.52530	**SBC**	8.325867
***p*-value**	0.000000	**DW statistic**	1.245326

e) Consumer Confidence predicting Business Confidence

Table A.5: Stability tests for BCI predicted by CCI

Variable	Coefficient	SE	*t*-Statistic	*p*-value
6/01/1982 - 6/01/1990 -- 33 obs				
CCI	1.252718	0.180804	6.928587	0.0000
C	44.35336	2.236204	19.83422	0.0000
9/01/1990 - 9/01/2001 -- 45 obs				
CCI	1.136354	0.216619	5.245867	0.0000
C	31.48930	1.957043	16.09024	0.0000
12/01/2001 - 12/01/2007 -- 25 obs				
CCI	0.803908	0.273029	2.944401	0.0038
C	65.11649	4.017476	16.20831	0.0000
3/01/2008 - 3/01/2017 -- 37 obs				
CCI	0.142564	0.158263	0.900807	0.3693
C	40.99462	1.264383	32.42262	0.0000

Adjusted R^2	0.609732	**AIC**	7.911854
S.E. of regression	12.29590	**SBC**	8.079948
***p* -value**	0.000000	**DW statistic**	1.379925

f) Business Confidence predicting Consumer Confidence

Table A.6: Stability tests for CCI predicted by BCI

Variable	Coefficient	SE	*t*-Statistic	*p*-value
6/01/1982 - 12/01/1987 -- 23 obs				
BCI	0.743469	0.116271	6.394296	0.0000
C	-29.32263	4.003470	-7.324304	0.0000
3/01/1988 - 6/01/1994 -- 26 obs				
BCI	0.244883	0.053428	4.583424	0.0000
C	-10.13958	2.371500	-4.275597	0.0000
9/01/1994 - 9/01/1999 -- 21 obs				
BCI	0.337705	0.046222	7.306104	0.0000
C	-6.231960	1.935137	-3.220422	0.0016
12/01/1999 - 12/01/2004 -- 21 obs				
BCI	0.221895	0.111852	1.983828	0.0494
C	-13.58856	6.264728	-2.169059	0.0319
3/01/2005 - 12/01/2011 -- 28 obs				
BCI	0.304519	0.044009	6.919540	0.0000
C	-5.156143	2.661474	-1.937326	0.0549
3/01/2012 - 3/01/2017 -- 21 obs				
BCI	0.562411	0.176235	3.191267	0.0018
C	-28.86683	7.639249	-3.778752	0.0002

Adjusted R^2	0.688340	**AIC**	6.516213
S.E. of regression	6.039127	**SBC**	6.768353
***p*-value**	0.000000	**DW statistic**	1.976704

Appendix C: Lag Length Selection

The * indicates the lag with the lowest information criteria.

Table A.7: Information Criteria results for Lag Selection: HC predicted by CCI

Household Consumption predicted by Consumer Confidence						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SBC**	**HQ**
0	-2199.68	NA	1.19E+12	33.47993	33.69833	33.56868
1	-1834.93	690.8062	5.03E+09	28.01409	28.31984	28.13833
2	**-1819.49**	**28.77259**	**4.23E+09**	**27.84077**	**28.23388***	**28.00051***
3	-1817.55	3.556359	4.37E+09	27.87199	28.35245	28.06723
4	-1813.83	6.705885	4.39E+09	27.87624	28.44406	28.10698
5	-1807.19	11.78116*	4.22e+09*	27.83615*	28.49133	28.10239
6	-1804.49	4.701148	4.30E+09	27.85588	28.59842	28.15761
7	-1801.59	4.964552	4.38E+09	27.87255	28.70245	28.20978
8	-1796.1	9.238928	4.29E+09	27.84992	28.76718	28.22265

Table A.8: Information Criteria results for Lag Selection: CCI predicted by HC

Consumer Confidence predicted by Household Consumption						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SBC**	**HQ**
0	-2205.8	NA	1.27E+12	33.54239	33.7171	33.61338
1	-1838.32	7.02E+02	5.14E+09	28.03515	28.29722	28.14164
2	**-1821.47**	**3.17E+01**	**4.23E+09**	**27.84049**	**28.18992***	**27.98249***
3	-1819.09	4.41E+00	4.33E+09	27.86499	28.30177	28.04248
4	-1815.61	6.32E+00	4.37E+09	27.8729	28.39705	28.08589
5	-1808.72	12.32223*	4.19e+09*	27.82908*	28.44059	28.07757
6	-1806.3	4.25E+00	4.29E+09	27.85307	28.55193	28.13706
7	-1803.92	4.11E+00	4.40E+09	27.87762	28.66384	28.1971
8	-1798.54	9.13E+00	4.32E+09	27.85668	28.73026	28.21166

Table A.9: Information Criteria results for Lag Selection: CF predicted by BCI

Capital Formation predicted by Business Confidence						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SBC**	**HQ**
0	-1798.12	NA	2.63E+09	27.36541	27.54013	27.43641
1	**-1549.09**	**475.4135**	**6.42E+07**	**23.6529**	**23.91497***	**23.75939**
2	-1546.21	5.408694	6.53E+07	23.66988	24.01931	23.81188
3	-1531.35	27.47451	5.54E+07	23.50529	23.94208	23.68278
4	-1524.36	12.70566	5.30E+07	23.46001	23.98416	23.673
5	-1512.82	20.63607*	47279450*	23.34574*	23.95724	23.59423*
6	-1511.28	2.696861	4.91E+07	23.3831	24.08196	23.66708
7	-1509.62	2.881511	5.09E+07	23.41843	24.20464	23.73791
8	-1504.86	8.074485	5.04E+07	23.40694	24.28051	23.76192

Table A.10: Information Criteria results for Lag Selection: BCI predicted by CF

Business Confidence predicted by Capital Formation						
Lag	LogL	LR	FPE	AIC	SBC	HQ
0	-1786.12	NA	2.26E+09	27.21394	27.43233	27.30268
1	**-1548.38**	**4.50E+02**	**6.55E+07**	**23.67239**	**23.97814***	**23.79663**
2	-1545.85	4.71E+00	6.69E+07	23.69467	24.08778	23.85442
3	-1530.7	2.78E+01	5.66E+07	23.5257	24.00617	23.72094
4	-1523.68	1.27E+01	5.41E+07	23.48	24.04782	23.71073
5	-1511.93	20.83429*	48097857*	23.36253*	24.01771	23.62877*
6	-1510.01	3.35E+00	4.97E+07	23.39403	24.13657	23.69577
7	-1508.45	2.66E+00	5.16E+07	23.43112	24.26101	23.76835
8	-1503.23	8.79E+00	5.07E+07	23.41249	24.32975	23.78523

Table A.11: Information Criteria results for Lag Selection: BCI predicted by CCI

Business Confidence predicted by Consumer Confidence						
Lag	LogL	LR	FPE	AIC	SBC	HQ
0	-996.56	NA	13973.02	15.2206	15.39532	-996.56
1	-882.969	2.17E+02	2655.807	13.56013	13.82221	-882.969
2	**-873.168**	**1.84E+01**	**2432.767**	**13.47224**	**13.82167***	**-873.168**
3	-863.641	1.76E+01	2237.99	13.38851	13.82529	-863.641
4	-863.079	1.02E+00	2358.647	13.44059	13.96474	-863.079
5	-854.506	15.32799*	2202.055	13.3713	13.9828	-854.506
6	-849.931	8.04E+00	2184.693*	13.36259*	14.06145	-849.931
7	-849.435	8.57E-01	2306.177	13.41568	14.2019	-849.435
8	-847.194	3.80E+00	2371.508	13.44233	14.31591	-847.194

Table A.12: Information Criteria results for Lag Selection: CCI predicted by BCI

Consumer Confidence predicted by Business Confidence						
Lag	LogL	LR	FPE	AIC	SBC	HQ
0	-1002.01	NA	16126.57	15.36385	15.62593	-1002.01
1	**-869.535**	**2.49E+02**	**2302.491**	**13.4172**	**13.76663***	**-869.535**
2	-859.943	1.77E+01	2116.026	13.33247	13.76926	-859.943
3	-852.374	1.38E+01	2005.482*	13.27839*	13.80253	-852.374
4	-851.455	1.64E+00	2102.572	13.32507	13.93657	-851.455
5	-845.655	10.19356*	2047.636	13.2978	13.99666	-845.655
6	-842.827	4.88E+00	2086.463	13.31556	14.10178	-842.827
7	-842.152	1.15E+00	2197.073	13.36593	14.23951	-842.152
8	-840.686	2.44E+00	2286.682	13.40433	14.36527	-840.686

References

Alimi, S and Ofonyelu, C. (2013). Toda-Yamamoto Causality Test Between Money Market Interest Rate And Expected Inflation: The Fisher Hypothesis Revisited. *European Scientific Journal.* 9(1). pp. 125-142.

Antoshin, S, Berg, O and Souto, M. (2008). Testing for Structural Breaks in Small Samples. *IMF Working Paper*. International Monetary Fund.

Awe, O.O. (2012). On Pairwise Granger Causality Modelling and Econometric Analysis of Selected Economic Indicators. *Interstat Journal (USA)*, 17(5), pp. 1-17.

Beaudry, P. and Portier, F. (2006). Stock Prices, News, and Economic Fluctuations. *American Economic Review*, 96(4), pp.1293-1307.

Boero, G. (2009). Trends and DF tests. *Department of Economics*, University of Warwick.

Box, G and Jenkins, G. (1970) *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day.

Bram, J. and Ludvigson, S. (1998). Does Consumer Confidence Forecast Household Expenditure? A sentiment index horse race. *Federal Reserve Bank of New York*.

Carroll, C. D., Fuhrer, J. C. and Wilcox, D. W. (1994). Does Consumer Sentiment Forecast Household Spending? If So, Why? *The American Economic Review*, 84(5), pp. 1397-1408.

Chutel, L. (2017). South African consumers are approaching Apartheid-era levels of pessimism. [online] *Quartz*. Available at: https://qz.com/1028071/south-african-consumers-are-approaching-apartheid-era-levels-of-pessimism/ [Accessed 2 Aug. 2017].

Croushore, D. (2005), Do Consumer Confidence Indexes Help Forecast Consumer Spending in Real Time? *North American Journal of Economics and Finance*. 16. pp.435-450.

Dees, S. and Soares Brinca, P. (2013). Consumer confidence as a predictor of consumption spending: Evidence for the United States and the Euro area. *International Economics*, 134, pp.1-14.

Dettling, M. (2013). Applied Time Series Analysis. *Swiss Federal Institute of Technology Zurich*.

Engle, R.F. and Granger C.W.J. (1987). Co-integration and error correction: representation, estimation and testing. *Econometrica*. 55. pp. 251-276.

European Central Bank. (2013). Confidence indicators and economic developments. *ECB Monthly Bulletin*. European Central Bank. January 2013.

Feridun, M. (2009). Unit Roots, Structural Breaks and Cointegration Analysis: A Review of the Available Processes and Procedures and an Application. *Faculty of Business and Economics Eastern Mediterranean University*.

Fin24. (2017). SA economy its own worst enemy - analysts. Available at: *http://www.fin24.com/economy/sa-economy-its-own-worst-enemy-analysts-20170607?mobile=true* [Accessed 7 Jun. 2017].

Foresti, P. (2007). Testing for Granger Causality Between Stock Prices and Economic Growth. *Munich Personal RePEc Archive*.

Fuhrer, J. C. (1993). What Role Does Consumer Sentiment Play in the U.S. Macro economy? *New England Economic Review*. 1. pp.32-44.

Granger, C. and Ghysels, E. (2001). *Essays in econometrics*. Cambridge: Cambridge University Press.

Granger, C. W.J (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37, 1969, pp. 424–38.

Harvin, C and Pahlavani, M (2006). Testing for Structural Breaks in the Korean Economy 1980-2005: An Application of the Innovational Outlier and the Additive Outlier Models. *Faculty of Business - Economics Working Papers*. Department of Economics, University of Wollongong, 2006.

Johansen, S. (1988), Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control*, 12, pp. 231.54.

Johansen, S. and Juselius, K. (1990), Maximum Likelihood Estimation and Inference on Cointegration - with Applications to the Demand for Money. *Oxford Bulletin of Economics and Statistics*. 52(2), pp. 169–210.

Jouini, J. and Boutahar, M. (2005), Evidence on structural changes in U.S. time series. *Economic Modelling*. 22. pp. 391–422.

Kershoff, G. (2000). Measuring business and consumer confidence in South Africa. Available at: *https://www.ber.ac.za/Knowledge/pkDownloadDocument.aspx?docid=4128* [Accessed 26 Aug. 2017].

Keynes, J.M. (1936). The General Theory of Employment, Interest and Money. *Palgrave Macmillan*.

Khumalo, J. (2014). Consumer Spending and Consumer Confidence in South Africa: Cointegration Analysis. *Journal of Economics and Behavioral Studies*. 6(2). pp. 95-104.

Koekemoer, R. (1999). Private Consumption Expenditure in South Africa: The Role of Price Expectations and Learning. University of Pretoria.

Kozhan, R. (2009). *Financial Econometrics - with Eviews*, Roman Kozhan & Ventus Publishing.

Lahiri, K., Monokroussos, G. and Zhao, Y. (2012). Forecasting consumption in real time: The role of consumer confidence in surveys. *Department of Economics*. University at Albany.

Leduc, S (2010). Confidence and the Business Cycle. *FRBSF Economic Letter*. Federal Reserve Bank of San Francisco.

Ludvigson, S. C. (2004). Consumer Confidence and Consumer Spending. *Journal of Economic Perspectives*, 18(2), pp.29 – 50.

Mabena, S. (2017). Three out every four rands spent by SA households' is on consumption expenditure. Available at: *http://www.sowetanlive.co.za/news/2017/01/27/three-out-every-four-rands-spent-by-sa-households-is-on-consumption-expenditure* [Accessed 26 Aug. 2017].

Mail and Guardian. (2012). Over 2.8m working days lost during strikes in 2011. Available at: *https://mg.co.za/article/2012-08-08-labour-strikes-working-days-lost* [Accessed 2 Sep. 2017].

Mail and Guardian. (2014). Numsa members embark on 'indefinite strike action'. Available at: *https://mg.co.za/article/2014-06-26-numsa-members-embark-on-indefinite-strike-action* [Accessed 2 Sep. 2017].

Murray, M. (1994). A drunk and her dog: an illustration of cointegration and error correction. *The American Statistician*, 48, pp. 37-39.

Özerkek, Y. and Çelik, S. (2010). The link between government spending, consumer confidence and consumption expenditures in emerging market countries. *Panoeconomicus*, 57(4), pp.471-485.

Perron, P (1989). The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica*, 57(6), pp. 1361-1401.

Perron, P. (1994). Trend, unit root and structural change in macroeconomic time series, *Cointegration for the Applied Economist,* Palgrave Macmillan, London.

Rossi, E (2009). Impulse Response Functions. *University of Pavia*.

South African Reserve Bank (2017). *Quarterly Bulletin*. South African Reserve Bank. March 2017.

Souleles, N. S. (2003). Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys. *Journal of Money, Credit, and Banking*, 36(1), pp.39–72.

Ssekuma, R (2011). A Study of Cointegration Models with Applications. *University of South Africa.*

Statistics South Africa. (2016). Expenditure on Gross Domestic Product: Sources and Methods. *Statistics South Africa: National Accounts division*.

Stock, J.H. and Watson, M.W. (2006) *Introduction to Econometrics*, 2nd edn, Boston: Addison-Wesley.

Triacca, U. (2014). Stationary stochastic processes. *University of L'Aquila Econometrics*.

Yeo, T. (2017). S.Africa: Nuclear build essential for sustained economic growth and development. *ESI Africa*.