THE RELATIONSHIP BETWEEN HOUSEHOLD CONSUMPTION EXPENDITURE, DISPOSABLE INCOME AND INDEBTEDNESS IN SOUTH AFRICA: AN APPLICATION OF THE VECTOR ERROR CORRECTION APPROACH

By

AZWIFARWI RICHARD KHANGALE

STUDENT NO: 8600306

A Dissertation

Submitted for the degree of

MASTER OF COMMERCE IN ECONOMICS

Department of Economics

SCHOOL OF MANAGEMENT SCIENCES

UNIVERSITY OF VENDA

Supervisor: Dr. M.A. Dagume

Co-Supervisor: Dr. G. Dafuleya

April 2021

University of Venda
Creating Future Leaders

DECLARATION

I, Khangale Azwifarwi Richard (Student number: 8600306), hereby declare that the dissertation titled "The Relationship Between Household Consumption Expenditure, Disposable Income and Indebtedness in South Africa: An Application of the Vector Error Correction Approach", for the Master of Commerce degree at the University of Venda, hereby submitted by me, has not previously been submitted for a degree at this or any other university, and that it is my own work in design and execution. All reference materials contained herein have been duly acknowledged.

Signed… ARKhangale ………………………… Date 28 April 2021

Azwifarwi Richard Khangale

Student No: 8600306

ACKNOWLEDGEMENTS

This research is dedicated to my family, whose unwavering love helped me get through the most difficult parts of the research. Dr. Dagume, for his support and inspiration in this review, deserves my gratitude. We will always be grateful for his unwavering love.

ABSTRACT

In a demand-led economy like South Africa, household consumption expenditure is a major source of economic development. The availability of consumer credit has allowed consumption spending to play a more active role. This, however, is followed by a disconnect between household spending and disposable income. One potential cause of the observed disconnect, according to the relative income hypothesis, is households' proclivity to imitate contemporary consumption expectations set by others. The difficulties that have resulted from the disconnection influence the factors that affect household consumption expenditure. The aim of this study was to use time series data to empirically analyse the South African household consumption function. For this analysis, the variables chosen were household spending expenditures, disposable income, and debt service burden for the years 1969 to 2019. The thesis was carried out using the Vector Error-Correction technique. The Augmented Dick-Fuller (ADF) and Philips-Perron (PP) tests were used to determine stationarity. Consumption expenditure and disposable income were found to be nonstationary at levels, they became stationary after first differencing. To assess the long-run relationship and assess the roles played by the three variables in achieving equilibrium after a shock, the Johansen Cointegration approach was used. Both disposable income and debt burden have a positive relationship with consumption spending. Furthermore, according to the findings, consumption spending does all the adjusting after a shock and does so slowly. The positive, though weak, relationship between consumption expenditure and debt burden is a noteworthy outcome. In South Africa, disposable income was found to have a positive impact on household consumption spending. As a result, the study suggests that the South African government consider implementing a basic income grant to help relieve the effects of high unemployment and poverty. Given that most people invest a substantial portion of their discretionary income on consumption, the government's revenue in the form of taxation would help to alleviate the fiscal burden

Keywords: Household consumption expenditure, disposable income, debt-service ratio, Vector Error-Correction Modelling, South Africa

TABLE OF CONTENTS

DECLARATION i
ACKNOWLEDGEMENTS ii
ABSTRACT iii
TABLE OF CONTENTS iv
LIST OF TABLES viii
LIST OF FIGURES ix
LIST OF ABBREVIATIONS x
CHAPTER 1 1
INTRODUCTION AND BACKGROUND OF THE STUDY 1
1.1 INTRODUCTION 1
1.2 BACKGROUND OF THE STUDY 1
1.3 PROBLEM STATEMENT 4
1.4 AIM OF THE STUDY 6
1.5 OBJECTIVES OF THE STUDY 6
1.6 RESEARCH QUESTIONS 6
1.7 JUSTIFICATION OF THE STUDY 6
1.8 DELIMITATION OF THE STUDY 7
1.9 OPERATIONAL DEFINITION OF TERMS 8
1.9.1 A Vector Auto Regression (VAR) model 8
1.9.2 Debt service burden 8
1.9.3 The Impulse Response Function 8
1.9.4 The Forecast Error Decomposition 8
1.10 ORGANIZATION OF THE STUDY 8
1.11 SUMMARY 9
CHAPTER 2 10
AN OVERVIEW OF HOUSEHOLD SECTOR IN SOUTH AFRICA 10
2.1 INTRODUCTION 10
2.2 DEVELOPMENT OF HOUSEHOLD SECTOR IN SOUTH AFRICA 10
2.2.1 Household consumption expenditure trend in south Africa 10
2.2.2 Household disposable income trend in South Africa 11
2.2.3 Household debt trend in South Africa 12
2.2.3.1 Debt- to -income ratio 14
2.2.3.2 Debt-service ratio 15

2.3 ACCOUNTING FOR HOUSEHOLD SECTOR DEBT ACCUMULATION IN SA 15
2.4 SUMMARY 15
CHAPTER 3 16
LITERATURE REVIEW 16
3.1 INTRODUCTION 16
3.2 THEORETICAL LITERATURE REVIEW 16
3.2.1 Keynesian Theory (Absolute Income Hypothesis) 16
3.2.2 Relative Income Hypothesis 17
3.2.3 Life – Cycle Hypothesis 18
3.2.4 Permanent Income Hypothesis 19
3.2.5 Random Walk Model 20
3.3 FRAMEWORK FOR HOUSEHOLD DEBT AND CONSUMER EXPENDITURE 20
3.4 EMPIRICAL LITERATURE REVIEW 22
3.5 SUMMARY 26
CHAPTER 4 27
RESEARCH METHODOLGY 27
4.1 INTRODUCTION 27
4.2 RESEARCH PARADIGM 27
4.3 RESEARCH DESIGN 28
4.4 RESEARCH APPROACH 28
4.5 SAMPLE, SAMPLING TECHNIQUE AND SAMPLING FRAME 29
4.5.1 Population of the study 29
4.5.2 Target Population 29
4.5.3 Sampling Strategy 29
4.5.4 Sample Size 30
4.6 DATA COLLECTION PROCEDURES 30
4.7 DATA ANALYSIS 30
4.8 MODEL SPECIFICATION 30
4.8.1 DATA SOURCES AND DEFINITION OF VARIABLES 31
4.8.2 ESTIMATION TECHNIQUES 31
4.8.2.1 AUGMENTED DICKEY- FULLER (ADF) TEST 32
4.8.2.2 PHILLIPS- PERRON (PP) TEST 32
4.8.3 JOHANSEN TEST OF CO-INTEGRATION 33
4.8.4 WEAK EXOGENEITY 35
4.8.5 VECTOR ERROR CORRECTION MODEL (VECM) 36

4.8.6 IMPULSE RESPONSE FUNCTION (IRF) AND FORECAST ERROR VARIANCE DECOMPOSITION 38
4.8.6.1 IMPULSE RESPONSE FUNCTION 38
4.8.6.2 VARIANCE DECOMPOSITION 39
4.9 DIAGNOSTIC TESTS 40
4.10 ETHICAL CONSIDERATIONS 40
4.11 SUMMARY 40
CHAPTER 5 42
DATA ANAYSIS, RESULTS AND DISCUSSIONS 42
5.1 INTRODUCTION 42
5.2 DATA AND TIME SERIES DESCRIPTIONS 42
5.3 RESULTS OF UNIT ROOT TESTS 44
5.4 THE JOHANSEN COINTEGRATION TEST RESULTS 45
5.5 VECTOR ERROR CORRECTION MODEL (VECM) 48
5.5.1 ANALYSIS OF THE LONG-RUN RELATIONSHIP 48
5.5.2 SHORT-RUN RELATIONSHIPS 49
5.6 GRANGER CAUSALITY TESTS 49
5.7 IMPULSE RESPONSE ANALYSIS 50
5.8 VARIANCE DECOMPOSITION ANALYSIS 51
5.9 VECM DIAGNOSTIC TESTS 52
5.9.1 TEST FOR AUTOCORRELATION 53
5.9.2 HETEROSKEDASTICITY TEST 53
5.9.2 NORMALITY TEST 54
5.11 SUMMARY 54
CHAPTER 6 55
SUMMARY, FINDINGS, POLICY RECOMMENDATIONS, LIMITATIONS AND FUTURE RESEARCH. 55
6.1 INTRODUCTION 55
6.2 SUMMARY OF THE STUDY AND FINDINGS 55
6.3 POLICY RECOMMENDATIONS 56
6.4 LIMITATIONS 56
.6.5 FUTURE RESEARCH 56
6.6 SUMMARY 57
REFERENCES 58
APPENDICES 63
APPENDIX 1: UNIT ROOT TEST ADF 63

APPENDIX 2: LAG ORDER SELECTION....76
APPENDIX 3: COINTEGRATION TESTS....77
APPENDIX 4: ERROR CORRECTION MODEL....79
APPENDIX 5: DIAGNOSTIC TESTS....80
APPENDIX 6: VARIANCE DECOMPOSITION....84

LIST OF TABLES

Table 5.1: Unit root test based on Augmented Dicky- Fuller test and Phillips-Perron test ……………………………………………………………………………………………... 61

Table 5. 2: Lag order selection………………………………………………………… 77

Table 5.3. cointegration tests (Trace and Maximum eigenvalue tests)……………..78

Table 5.4. Error corrections results…………………………………………………….. 80

Table 5.5 Granger causality test…………………………………………………….. 51

Table 5.6. Impulse Response Function………………………………………………...84

Table 5.7. Variance Decomposition…………………………………………………… 85

Table 5.8. Autocorrelation tests………………………………………………………… 82

LIST OF FIGURES

Fig 2.1 Household Consumption Expenditure……………………………………….……….11

Figure 2.2 Household Disposable Income…………………………………………….12

Fig 2.2 Debt Income Ratio…………………………………………………………….14

Fig 2.3 Debt Service Ratio…………………………………………………………...14

Fig 5.1 Data Set Description………………………………………………………….43

LIST OF ABBREVIATIONS

ADF	**Augmented Dickey-Fuller**
AIH	**Absolute Income Hypothesis**
ARDL	**Autoregressive Distributed Lag Model**
HCE (C)	**Household Consumption Expenditure**
DSR (DB)	**Debt-Service Ratio**
CPI	**Consumer Price Index**
ECM	**Error Correction Model**
ECT	**Error Correction Term**
GDP	**Gross Domestic Product**
LCH	**Life-Cycle Hypothesis**
RIH	**Relative Income Hypothesis**
MPC	**Marginal Propensity to Consume**
SARB	**South African Reserve Bank**
VAR	**Vector Autoregressive Regression**
VECM	**Vector Error-Correction Model**
VDC	**Variance Decomposition**
STATS SA	**Statistics South Africa**
HDI (YD)	**Household Disposable Income**

CHAPTER 1

INTRODUCTION AND BACKGROUND OF THE STUDY

1.1 INTRODUCTION

Household debt levels in South Africa have been increasing for some time now. It has increased so much that discussions about its economic implications have attracted a great deal of attention of both policy makers and economists. According to the South African Reserve Bank (SARB, 2019), household debt increased at a faster rate in the fourth quarter of 2018. Household debt as a percentage of nominal disposable income edged higher from 71.8% in the third quarter of 2018 to 72.7% in the fourth quarter. Furthermore, the quarter-to-quarter increase in household debt exceeded the increase in the disposable income, however, debt-service cost to disposable income increased marginally to 9.3%, in the fourth quarter of 2018, from 9.1 in the third quarter. The concern of policy makers is the possibility of household debt accumulation reaching unsustainable level leading to buttressing of consumption spending, and by extension, aggregate demand.

1.2 BACKGROUND OF THE STUDY

The South African economy faces a deep-rooted structural flaw that is related fundamentally to stagnation of real wages for most wage earners and the concomitant increase in income inequality. The growth of households' indebtedness, however, has been able to maintain the momentum of South Africa's economic growth, notwithstanding these challenges. The very high debt-to-income ratio of households makes further debt accumulation highly unlikely, but, insufficient real wage growth will eventually lead the economy into turmoil. These challenges resonate with the work of Cynamon and Fazzari (2008), which attributed a major part of the United States' economic success before 2008 to the strong growth of American consumption. A concern was also raised that the credit-financed consumption will make the economy more fragile and vulnerable to demand shocks, such as trade wars.

Given that household consumption comprises more than 60 percent of the aggregate economic expenditure, consumer behaviour is one of the most researched areas in economics. It, therefore, stands to reason that, wide differences in opinion continue to persist on how best to characterise the behaviour of consumption, empirically. For the purpose of this dissertation, we shall group these views into two broad schools of thought, as follows:

- one group emphasising the importance of defining optimal behaviour in a world of efficient financial markets, and
- the other focusing on the effect of financial market imperfections, the role of uncertainty, and the widespread use of simple “rules of thumb” to guide consumer behaviour (Bayar & Mc Morrow, 1999).

Athanasio (1995), explains that the two crucial elements in any analysis of consumption, are - the characterisation of agents’ preferences and the opportunity set. According to the choice theoretical models, given a certain set of preferences, income and price of goods, the problem facing the consumer is that of composing a basket of goods that will maximise his or her individual wellbeing (Santos, *et al.,* 2014). The rationality assumption dismisses both the process of decision-making and the determinants of consumption as irrelevant. This means that any analysis of the process of creating preferences remains outside the sphere of economics and is considered an individual matter, independent of context. The same approach is applied regarding decisions concerning credit and long-term consumption.

From the perspective of the life-cycle hypothesis Modigliani and Brumberg (1954), indebtedness at the beginning of a career is rational; this is because the expectation of a rise in income during professional life will enable individuals to support the burden of debt and, at a certain point, start saving for their retirement. Similarly, from the perspective of the permanent income hypothesis (Friedman, 1957), individuals consume a steady proportion of their permanent income, determined by their wealth and level of education, which in turn depends on their individual capacity to generate income during their lives (Santos *et al.,* 2014).

Even though the permanent income hypothesis does not indicate the point at which it is rational to resort to credit, like the life-cycle hypothesis, it, however, assumes that indebtedness is a result of a rational decision aimed at maximising intertemporal utility, based on the wealth and income expected during the life cycle. These analyses, it is argued, offer abstract arguments which aim to justify the rationality of credit and consumption decisions, devoid of the context. These analyses do not take cognisance of the fact that the relationship between households and the credit markets depends on a myriad of conditions, some of which restrain households from entering debt (Santos *et al.,* 2014).

In the light of this abundant evidence, it is logical to say that context matters. It also seems fair to say that Duseberry's relative income hypothesis rests on a more realistic model of human nature than the choice theoretic life cycle and the permanent hypotheses. Several empirical studies based on different theoretical frameworks lend support to the consumption behaviour predicted by Duesenberry's relative income hypothesis. As part of their effort, Kim *et al.* (2013), argue that Post-Keynesian economists have used the relative income hypothesis in their quest to understand household consumption behaviour and its relationship to debt accumulation. According to them, emulation effects are associated with quantitative and qualitative changes in household debt accumulation, as households pursue consumption targets that are incompatible with their real incomes.

Ravina (2007) found that consumption of the reference group is an important determinant of household consumption behaviour. The findings were made in her study based on estimations of the Euler equations associated with intertemporal optimization by a representative household. Cynamon and Fazzari (2008), meanwhile provide a detailed explanation of this behaviour based on the notion that consumer preferences endogenously evolve in a world of social cues. Drawing on insights of the relative income hypothesis, they argue that households tend to learn consumption patterns from social reference groups. As a case in point, they argue that the United States household debt accumulation, since the 1980s, is partly due the expansion of people's social reference groups.

Notwithstanding the important role played by the relative income hypothesis in understanding recent patterns of consumption behaviour and debt accumulation, little attention has been paid to the development of a formal theory of consumption based on its insight. This dissertation, therefore, seeks to estimate the South African aggregate consumption function that draws on the Keynesian's absolute income and Duseberry's relative income hypotheses. This approach is also based on the insights of researchers, such as Cynamon and Fazzari's (2008) on the interplay and dynamics of borrowing, debt accumulation and consumption expenditure.

To this end, we will estimate a Vector Error Correction Model (VECM), where consumption, disposable income and borrowing are modelled jointly, and test whether consumption reacts when borrowing departs from its long-run determinants. Unlike in similar studies carried out in South Africa before, this dissertation also seeks to establish what the precise form of the co-integration system of consumption is, and what variables could be used as weak exogenous variables.

1.3 PROBLEM STATEMENT

The South African Reserve Bank has announced in its last quarter bulletin that household debt as a percentage of disposable income was 72.7 % as at the end of 2018. In addition, the debt–service cost to disposable income has increased from 9.1% in the third quarter to 9.3% in the fourth quarter of 2018 (SARB 2019). The biggest concern of policy makers is that debt-servicing costs, as a percentage of disposable income, is increasing and this has the potential of making households vulnerable to economic shocks, such as increase in interest rates.

Debt provides resources for financing household expenditure and permits consumption smoothing, however, the high level of household debt, as recently observed in South Africa, might also result in some risk. A high level of debt generally implies a high debt-service burden and restricts the ability of households to gain access to additional funding. A high level of debt raises households' vulnerability and reduces their ability to adjust when faced with unexpected shocks to their incomes, thus, expected and unexpected shocks may constrain household spending decisions.

According to the aggregate demand generating thesis, aggregate demand growth in many countries, South Africa included, has been generated by an increasingly unsustainable process which rests on, among other things, rising household debt. For example, household borrowing has offset the problem of aggregate demand, but just, when households are about, if not already, approaching debt ceilings, thus, the higher economic growth of the 2000s might have been built on a combination of forces that are unsustainable. These forces helped to cover up the contradictions between deteriorating income distributions and aggregate demand generation (Kukk, 2016).

It is now understood by both the policy makers and economists that the South African economy has experienced a structural flaw in its aggregate demand generating process. This flaw has been masked for some time by debt-financed consumer boom as the link between household debt and the real economy is household consumption. There are two different strands of theories explaining the effect of household debt on consumption (Kukk, 2016). One strand covers the intertemporal models represented by life cycle and permanent income hypotheses; they focus on their improved ability to smooth income shocks and reduce consumption volatility made possible by access to credit. The other strand highlights the increased vulnerability of households because of their increased indebtedness and the negative implications of household debt (Barba & Pivetti, 2009; Cynamon & Fazzari, 2008).

Given the observation that most of the growth on households' consumption expenditure in South Africa has been financed through borrowing, the current dissertation seeks to specifically investigate if there is a long-run relationship between household debt, disposable income, and consumption. This will be achieved through the examination of the dynamic relationships among these three variables, over both the short- and long-runs using the vector error correction modelling.

1.4 AIM OF THE STUDY

The aim of the study is to investigate the relationship between household consumption, disposable income and indebtedness in South Africa using the Vector Error Correction Model.

1.5 OBJECTIVES OF THE STUDY

The following objectives will be used to realise the aim of the study:

- To analyse the sensitivity of consumption expenditure to changes in disposable income.
- To assess the extent to which the debt-service burden is helpful in explaining the disconnection between disposable and consumption expenditure, bearing in mind the fact that, debt can have asymmetric effects on consumption, and
- To determine the relative roles of disposable income and debt-service burden in the consumption function (both as short-run and long-run dynamics).
- To make policy recommendations for increasing household consumption spending in South Africa.

1.6 RESEARCH QUESTIONS

For the purpose of this study, the following questions will be addressed.

- What is the impact of disposable income on household consumption expenditure?
- What is the effect of household debt-service burden on household consumption expenditure?
- What policy options are available in South Africa to increase household consumption expenditure?

1.7 JUSTIFICATION OF THE STUDY

It is crucial to address the issue of rising household debts because of the risks it poses to macroeconomic development and financial stability. It has been observed that highly indebted households tend to reduce their spending more than their less-indebted peers, in times of stress. In this study the impact of household debts on South

African households' consumption will be analysed. The power of fiscal policy to influence the economy – as expressed by the fiscal policy multiplier – arises from the feedback between income and consumption. It is, therefore, important for policymakers to understand the main determinants of consumption expenditure. A thorough time series analysis of aggregate consumption behaviour is valuable because the correct estimation of the marginal propensity to consume (MPC) is essential for macroeconomic policy formulation.

The aggregate private consumption expenditure accounts for more than half of an economy's GDP. Besides accounting for a significant share of the GDP, consumption represents one of the central tax bases, therefore, understanding its determinants is vital for policymakers. A case in point, is the concern expressed by Parliament in its Quarterly Economic Brief (2017) about high level of household indebtedness, where it was argued that a correction of the situation could significantly decrease consumption, as this will have a negative impact on both economic growth and tax revenue. The importance of consumption in macroeconomics has made it one of the most studied aggregate expenditure relationships. Consumption function has become a central part of macroeconomic modelling; hence, structural forms of consumption functions and theories are fulcrums of macroeconomic policies and analyses.

1.8 DELIMITATION OF THE STUDY

This study will adopt a dynamic vector autoregressive regression (VAR), which explores co-integration. The essence of the study is to capture the causal dynamic relationships between consumption expenditure, disposable income and debt-service burden, as well as, to observe the long and short run dynamics, given a VAR with possible long run co-integration, amongst a set of variables of interest, mentioned above.

1.9 OPERATIONAL DEFINITION OF TERMS

1.9.1 A Vector Auto Regression (VAR) model

A VAR is an n-equation, n-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining n-1 variables (Enders, 2015).

1.9.2 Debt service burden

A debt service burden (debt payment to income ratio) is a measure of a household's debt burden, reflecting the relative allocation of household resources on borrowing commitment. The ratio is derived on an annual basis, which allows for the examination of household debt burden within a fixed time period of one year. It serves as proxy for the effect of household borrowing, on consumption expenditure (Enders, 2015).

1.9.3 The Impulse Response Function

An impulse response function traces the response of current and future values of each of the variables to a one-unit increase in the current value of one of the VAR errors, if this error returns to zero in subsequent periods, then all other errors are equal to zero (Enders, 2015).

1.9.4 The Forecast Error Decomposition

The forecast error decomposition is the percentage of the variance of the error made in the forecasting of a variable (for example, inflation) due to a specific shock (for example, the error terms in the unemployment equation) at a given horizon (for example, two years (Enders, 2015).

1.10 ORGANIZATION OF THE STUDY

The study consists of six (6) chapters. Chapter one serves as an introduction to the study and highlights the statement of the problem, research questions, objectives, study justification, delimitations, limitations of the study and the organization of the study. Chapter two provides the overview of the trends pertaining to the household sector regarding household consumption expenditure, household disposable income and household debt. Chapter three reviews the existing literature on consumption. It includes the following: theories of consumption and empirical review of the relationship between disposable income, indebtedness and household consumption. Chapter four outlines the methodology to be followed in the study. The chapter describes the method of the study, model specification, definition of variables, as well as estimation of procedures. For the purpose of this study, the researcher will jointly model consumption, disposable income and debt-service burden using a Vector Error Correction Model. Chapter five covers the presentation, interpretation and analysis of the data collected. Chapter six provides closure for the study, by providing a summary of the findings, recommendations, limitations and prospective future areas of research.

1.11 SUMMARY

This chapter provides an introduction and background of the research, inclusive of the research focus and the rationale. The discussions outline the problem statement (the reason why the research has decided to embark on this study) and an overview of the methodological approach (what will guide the researcher in carrying out this study).

CHAPTER 2

AN OVERVIEW OF HOUSEHOLD SECTOR IN SOUTH AFRICA

2.1 INTRODUCTION

This chapter focuses on the overview of the trends pertaining to the household sector regarding household consumption expenditure, household disposable income and household debt.

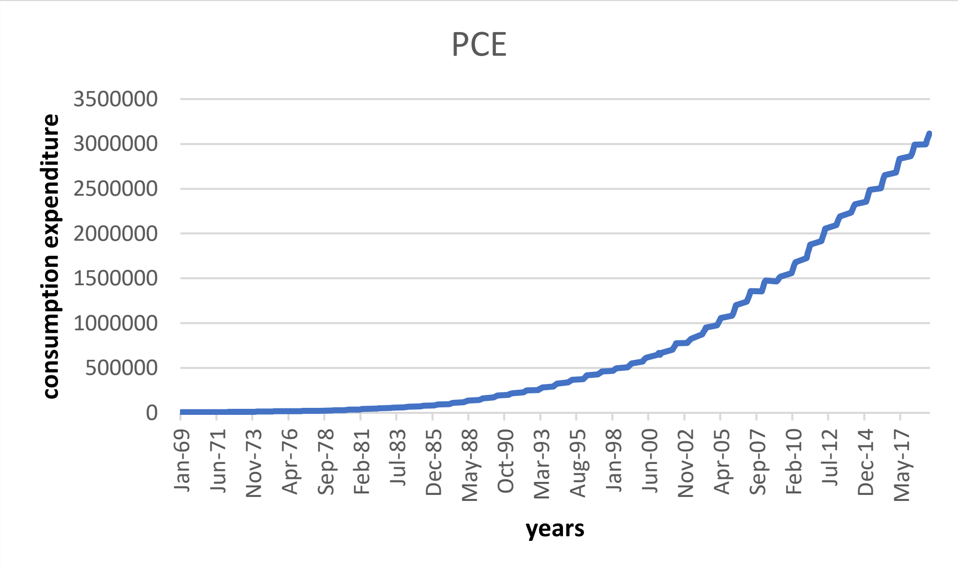
2.2 DEVELOPMENT OF HOUSEHOLD SECTOR IN SOUTH AFRICA

2.2.1 Household consumption expenditure trend in south Africa

Household consumption is the single largest contributor to economic activity in South Africa from the expenditure side. As such, the financial health of households and confidence in their prospects are of critical importance. The 0.8% quarter-on-quarter drop in household consumption spending in the first quarter of 2019 contributed -0.5% to the 3.2% contraction in overall GDP. The weakness in consumer spending is rooted in various factors such as real disposable income levels, existing household debt and the cost of servicing such debt, access to further credit, as well as employment prospects, all of which influence the ability and willingness of households to spend (IDC,2019).

Consumption expenditure grew by 1 per cent in the first half of 2019 compared with the corresponding period of 2018. Although household spending remains the main support for growth, spending on non-essential items has fallen dramatically due to rising unemployment, successive fuel price hikes and tax increases. Retailers are responding by keeping prices low and margins tight. A mild acceleration in consumption is forecast over the medium term as employment and income growth are expected to recover only gradually (Mboweni,2019)

Household consumption spending remained subdued during last year, affected by moderate growth in real disposable incomes, high levels of indebtedness and poor employment creation. In real terms, retail trade sales rose by 1.2% - the slowest rate of increase in a decade. This reflected low confidence levels amongst consumers, which fell sharply during 2019. However, a lower interest rate and inflation environment should provide some relief to the households going forward (IDC,2020). The rebound in household consumption expenditure in the third quarter of 2020 resulted from sizeable increases in real outlays on durable, semi-durable and non-durable goods, which reflected resurgent demand from a very low base as restrictions on the sale of these goods were lifted. Spending on consumer services recovered at a slower pace, impacted by the remaining restrictions on large social gatherings and international travel, with consumers likely redirecting some of their service-orientated budgets to meet pent-up demand for goods. The turnaround in real expenditure by households was consistent with the rebound in real disposable income in the third quarter of 2020, notwithstanding rising unemployment and low consumer confidence (SARB,2020). Figure 2.1 shows the growth of consumption expenditure rising steadily from the 1980s up to the 2000s, from henceforth, the consumption expenditure growth was subdued.

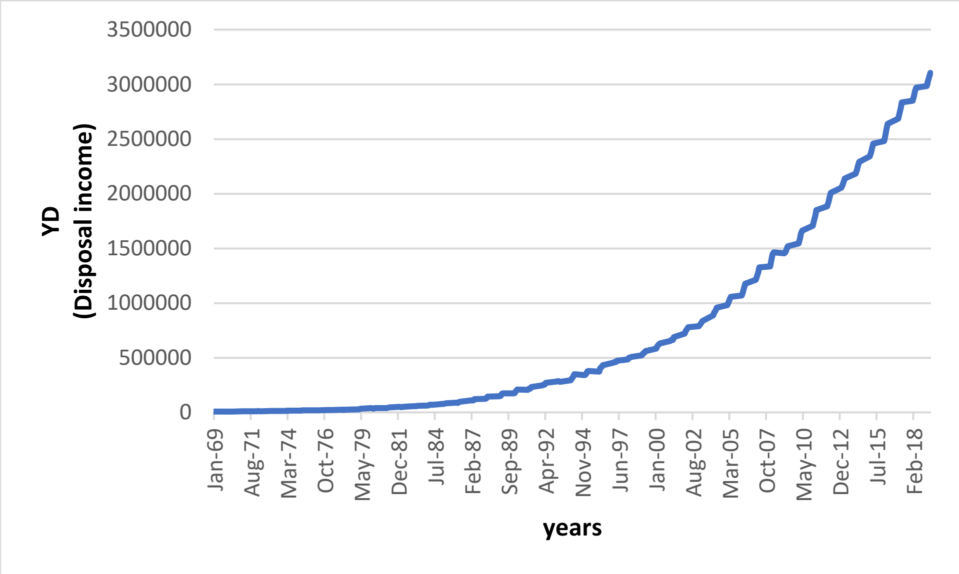


Data source: SARB (2019)

Figure 2.1: Household consumption expenditure in South Africa (1969-2019)

2.2.2 Household disposable income trend in South Africa

Household disposable income increased by 0.6% in real terms in 2018, providing limited scope for increased spending. Household debt levels remain high, representing 72.7% of disposable income in the final quarter of 2018. The affordability of such debt is reflected in debt servicing costs, that is the interest payments made by households on their outstanding debt. At 9.3%, the debt servicing cost of households is significantly above the long-term average of 7.7%, hence their reluctance to incur additional debt. Slow-rising disposable income, high indebtedness and debt-servicing costs indicate that households do not have much room to increase their spending activity, at least in the near- to short-term (IDC,2019). The household disposable income shares the same trend with the household consumption expenditure as displayed on figure 2.2.



Data source: SARB (2019)

Figure 2.2: Household disposable income in South Africa (1969-2019)

2.2.3 Household debt trend in South Africa

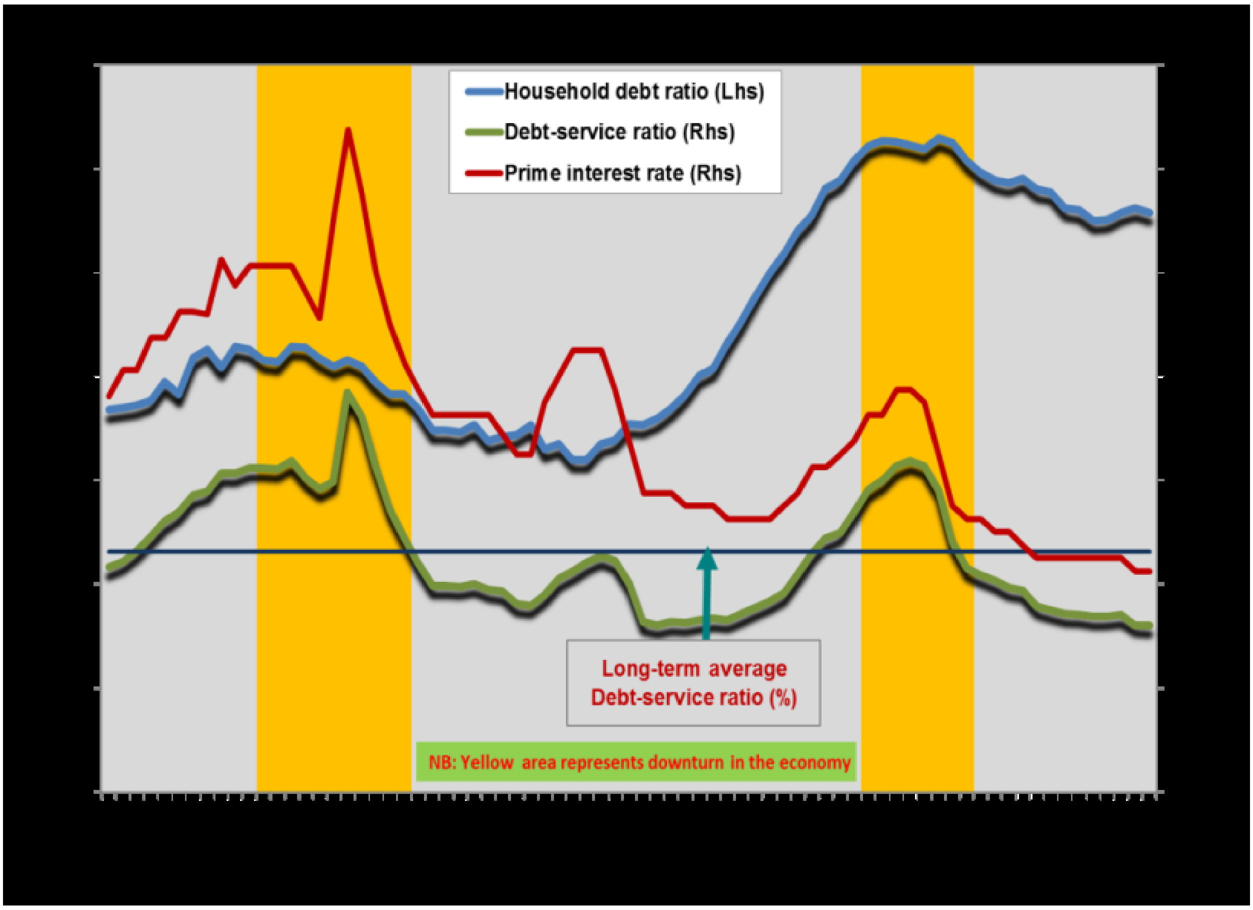
Understanding the development of household debt is important as it influences consumption expenditure, the biggest component of the country gross domestic product. Changes in financial markets such as financial regulation and liberalization aided and abated household sector debt accumulation. The ensued financial deepening was accompanied by stronger household demand for credit. The household debt burdens proxied by ratios such as debt-to-income and debt-service ratios are high. According to Zabai (2017), assessment of the implications of household debt burdens is imperative in case they experience income shocks without the requisite income buffers.

To discern the vulnerability of the households the assessment their balance sheet composition may be the point of departure (MISHKIN, 1978) Subsequently, the forces that underline or underscores the level and growth dynamics of household debt need to be established. And both macroeconomic and microeconomic perspectives are important for proper understanding of household debt and its implications on the economy.

At low interest environment, rising real disposable incomes, increased job creation and ease of access to credit supported the strong growth in household consumption expenditure over the period 2004 to 2007. Spending on durable goods (incl. motor vehicles, furniture and another household equipment) expanded at a very rapid pace. This excessive consumption was partly driven by increased access to credit, resulting in a steep rise in household debt. The debt-to-disposable income ratio increased sharply from 52% in the final quarter of 2002 to an all-time high of 82.7% by the first quarter of 2008. Although debt levels have receded slightly (assisted by the introduction of the National Credit Act in 2008), households remain highly indebted as their debt represented 75.8% of their disposable income by the final quarter of 2012(IDC,2013).

Increased consumption expenditure has also been reflected in a substantial deterioration in household savings over the years. The savings-to-disposable income ratio had stood at 2.7% in 1994, but a continued deterioration ensued in subsequent years, with this ratio falling to 0% by 2012. Over the period 2006 to 2011, households made a negative contribution to the national savings pool, as increased levels of dissaving's were reported. Simultaneously, household indebtedness rose sharply from 64.3% of disposable income in 2005 to an all-time high of 82.4% by 2008, but subsequently declined to 75.6% by 2012(IDC,2013).

Household debt increased in the third quarter of 2020 following an unprecedented decline in the second quarter. However, household debt as a percentage of nominal disposable income decreased from 86.5% in the second quarter of 2020 to 75.7% in the third quarter, as the increase in household disposable income exceeded that in debt (Fig 2.3). Households' net wealth increased further in the third quarter of 2020, albeit at a slower pace, as the increase in total assets outweighed that in total liabilities. The value of household assets increased despite the FTSE/JSE All-Share Price Index (Alsi) remaining broadly unchanged in the third quarter of 2020 after it recovered notably in the second quarter (SARB,2020).



Source: IDC, Compiled from SARB data

Figure 2.3: Household debt and the debt service ratio trends in South Africa (1994-2012)

Following our review of the various aspects and patterns of household debt, we must now define and examine some of the approaches used to assess the burden of household debt. The debt-to-income ratio and the debt-service ratio are two examples.

2.2.3.1 Debt- to -income ratio

It is used as an illustrative measure of risk. Rising household debt to income ratio illustrate how large a part of household income is required to service the debt. Household debt in South Africa increased from 71.90% in 2018 to 72.80%0f gross income in 2019(Trading Economics, 2020). The debt-to-income ratio above shows the rising trend of household debt that increases more rapidly than the corresponding household income since 2006.

2.2.3.2 Debt-service ratio

As already alluded to, one of indicator used to measure the household debt burden is the debt-service ratio. It measures the portion of disposable income required to meet debt obligations. The South African debt-service ratio was reported at 9.200% in March 2020. That recorded a marginal increase from the previous 9.00% for December 2019 (Trading Economics, 2020).

2.3 ACCOUNTING FOR HOUSEHOLD SECTOR DEBT ACCUMULATION IN SA

Household liquidity constraints were eased as a result of financial liberalization and deregulation, allowing them to borrow to increase consumption. As a result, the 1980s financial liberalization appears as a possible reason for increasing household debt (Barba & Pivetti, 2009). The controversy about how households make choices, on the other hand, continues. Households are rational people, according to the neoclassical school, whereas Post-Keynesians believe that their choices are conditioned by the environment they live in. The fact that the patterns of consumer spending and household debt have varied significantly across countries supports this (Stockhammer, 2010). Via a variety of channels, financial liberalization and deregulation have expanded and deepened the financial system. More financial instruments were created as a result of the shadow banking and financial developments that followed, as well as an increase in the availability of credit through innovative packaging.

2.4 SUMMARY

To quote Wolf and Resnick (2012: 80), "any individual's behaviour is understood as the result of various and multiple determinants arising from all the natural, cultural, political, and economic processes that make up the total context into which we are all born and where our lives converge to make us what we are at each moment." Individual action, whether economic or otherwise, is therefore overdetermined by any of these processes; it cannot be reduced to the influence of either one or a subset of them.” The household debt accumulation is a function of many variables, as such it cannot be reduced to any factors and differs from one country to another.

CHAPTER 3

LITERATURE REVIEW

3.1 INTRODUCTION

This chapter examines the effect of household debt on consumer spending in South Africa through a systematic literature review. It includes a theoretical context as well as related literature on the evolution of household debt. The study would also provide the researcher with a variety of perspectives and methods for addressing the research intent and objectives.

3.2 THEORETICAL LITERATURE REVIEW

This section will cover the following consumption hypotheses: Keynesian Theory, Relative Income Hypothesis, Life-Cycle Hypothesis, Permanent-Income Hypothesis and Random Walk Model

3.2.1 Keynesian Theory (Absolute Income Hypothesis)

According to Keynes, the marginal propensity to consume is between zero and one, the average propensity to consume falls as income increases, and current income is the primary determinant of consumption. Despite the existence of many factors (both objective and subjective), current income plays a significant role in assessing current consumption (Mankiw, 1997). The Keynesian consumption function is frequently expressed as follows, based on these three conjectures:

$$C = a + bY, \ a>0, \ 0<b<1, \qquad (1)$$

C is the consumption, Y is the disposable income, a is a constant (autonomous consumption) while b is the marginal propensity to consume. Implicit in this model is the understanding that households are liquidity-constrained, therefore, cannot borrow to consume more than their current income allows (Landsem, 2010).

Keynes' hypotheses have been verified by studies of household consumption data and short time sequence. However, long-term studies have found no evidence that the average desire to consume decreases as income increases. Keynes' hypotheses have been verified by studies of household consumption data and short time sequence. However, long-term studies have found no evidence that the average desire to consume decreases as income increases. The Keynesian Absolute Income Hypothesis' theoretical and empirical shortcomings have led to the emergence of new theories based on micro foundations, such as the Lice-cycle and Permanent Income Hypotheses.

3.2.2 Relative Income Hypothesis

The relative income hypothesis (Duesenberry, 1949) posits that consumption has social and psychological foundations which are ratchet effect and demonstration effect. Duesenberry (1949) argues that the 'demonstration effect' is the basic mechanism that influences consumption, and it is based. based on households' preference for interdependence and consumption behaviour emulation to maintain eir social status (Mason, 200). Consequently, a household's consumption expenditure is, not conditional on their own income, rather it is dependent on income relative to other households (Cuadrado & Long, 2011).

Duesenberry's (1949) analysis of income relativity also relates to the circumstances compelling households to rely on debt. Households who happen to encounter a decrease in income, for whatever reason, use debt facilities to compensate for the loss in order to maintain their established positions in the consumption hierarchy. As such, debt enables households to maintain level of expenditures with their reference group (Mourad, 2014).

Thee 'ratchet effect' has a major bearing on consumption levels. It relates to the proclivity of a household's current consumption level being influenced by their peak income in previous periods; Households will seek to maintain consumption relative to standard achieved in the past. As the result, households sometimes use credit and debt to consume in excess of what their current income will allow. This is because habits are inevitably formed at the highest income level and bear a rigid significance on consumption levels for present and future periods. Should the subsequent declines in income be excessive, households will be forced either to de-cumulate their savings or rely on debt to finance their rigid level of consumption until their income rises or they reach their debt limit (Mourad, 2014).

3.2.3 Life – Cycle Hypothesis

The Life-cycle hypothesis (LCH) was developed by Modigliani and Brumberg (1954), to explain the apparently conflicting pieces of evidence that came to light when Keynes' consumption function was interrogated extensively. LCH posits that income varies systematically over the phases of a consumer's life cycle and savings allow the consumer to achieve smooth consumption. It argues that consumers maximise their incomes' utility over their lifespan, subject to their budget constraints, and therefore smooth consumption over their lifespan (Landsmen, 2010).

A consumer's lifetime resources are composed of initial wealth (W) and lifetime earnings (Y). Under the auspices of representative household, the aggregate consumption function is almost the same as the individual consumption function. As a result, the aggregate consumption function depends on both wealth and income. That is, the economy's consumption function is:

$$C = \alpha W + \beta Y \qquad (2)$$

where the parameter α is the marginal propensity to consume out of wealth, and the parameter β is the marginal propensity to consume out of income (Mankiw, 1997). According to the life-cycle consumption function, the average propensity to consume is expressed as follows:

$$C/Y = \alpha\,(W/Y) + \beta \qquad (3)$$

It follows that, because wealth (w) does not vary proportionally with income from person to person, we should find that high income corresponds to a low average propensity to consume when looking at data across individuals or over short periods of time. Over long periods of time, wealth and income grow together, resulting in a constant average propensity to consume (Mankiw, 1997).

The implication of LCH is that, consumption will barely respond to temporary changes in income, but that unexpected, permanent changes to income would lead to a proportional change in consumption. One of the criticisms levelled against LCH is that credit constraints due to lack of collateral will limit consumption of the young people (Landsmen, 2010).

3.2.4 Permanent Income Hypothesis

Friedman (1957) proposed the permanent income hypothesis (PIH) to explain consumer behaviour. The PIH argues that the most important factor determining consumption expenditure is permanent income. According to PIH, households determine permanent income within the framework of the adaptive expectation's hypothesis. Permanent income is the part of income that households expect to persist into the future, on the other hand, transitory income is part of the income that a household does not expect to persist. In other words, permanent income is average income, and transitory income is random deviation from the average (Mankiw, 1997).

Friedman reasoned that consumption should depend primarily on permanent income. This is because households use savings and borrowings to smooth consumption in response to transitory changes in income. He concluded that we should view the consumption function as an approximate figure:

$$C = \alpha Y^p \tag{4}$$

where α is a constant and Y^p is the permanent income. The PIH, as expressed by this equation, states that consumption is proportional to the permanent income (Mankiw, 1997: 426). According to PIH, consumption depends on permanent income, yet many studies on the consumption function try to relate consumption to current income. Friedman has argued that this errors-in-variables' problem, explains the seemingly contradictory findings (Mankiw, 1997).

Based on PIH, the average propensity to consume depends on the ratio of permanent income to the current income.

$$APC = C/Y = \alpha Y^p/Y \tag{5}$$

When current income temporarily rises above permanent income the average propensity to consume temporarily falls. Similarly, when current income temporarily falls below permanent income, the average propensity to consume temporarily rises.

It seems that the PIH is a useful benchmark for a study on consumption; its assumptions, which include perfect credit markets, absence of liquidity constraints, identical interest rate for borrowers and lenders, as well as perfect rationality of consumers, are too strong to hold. The presence of, for example, liquidity constraints means that current income matters more than permanent income, thus, with liquidity constraints, households do not smooth their consumption perfectly, which leads to the failure of the permanent income hypothesis.

3.2.5 Random Walk Model

Hall (1978) combined the life-cycle and permanent income models with the rational expectations, to conclude that consumption follows a random walk (RWM), that is, changes in consumption over time are unpredictable. The final equation of RWM with drift can be expressed in terms of a regression model as follows:

$$C_t = \beta C_{t-1} + \varepsilon_t \qquad (6)$$

The RWM hypothesis implies that there is no need for other variables for forecasting because all the information is already included in C_{t-1} decision and adding other variables have no predictive power and they will be statistically insignificant (Hall 1978). Another implication of Hall's RMW model is that consumption follows a martingale. This implies that changes in consumption should be uncorrelated with unanticipated changes in income. That is, $\varepsilon_{t-1}(\Delta C_t) = 0$.

Any past or otherwise predictable information should not help to forecast changes in consumption, therefore, current and past values of income, particularly, should have no predictable power whatsoever. Empirical studies on time series data, however, have rendered the above implications suspect. Rather, consumption has been observed to exhibit both excess sensitivity and excess smoothness to income.

3.3 FRAMEWORK FOR HOUSEHOLD DEBT AND CONSUMER EXPENDITURE

To overcome the limitations of permanent and life-cycle models, one procedure is to posit that consumption is a social process with sets of heterogeneous households (Cynamon & Fazzari,2008). The properties of these households include endogenously determined preferences partly contingent on other households' preferences and the former can alter their behaviour from sources emanating from society (Ravina, 2007).

These households would not maximise the static utility function by consuming from the permanent income, rather, they would depend on simple norms, such as consuming from current income and wealth. The presence of fundamental uncertainty is the main cause behind imposing this basic overarching structure on households' behaviour (Akerlof, 2007).

The predominant reliance on current income results in households succumbing to liquidity constraints, which arise from general fluctuations in income. Inter-household competition, to attain prestigious social status positions, can also render households constrained if required expenditure levels are greater than that of income levels. On that basis, the role of debt can be one of substituting for the inadequacy of the income across the life-cycle, in supporting household consumption (Akerlof, 2007).

On another level, the heights of the significant points in the income profile, as mostly determined by the wages, contribute to the likelihood that the household will rely on debt to achieve their consumption level. What gives rise to the inefficiency of income; hence, high-level debt accumulation is the aspired standard of living. The standard of living conceived of as the desired level of consumption, sets the parameters for reliance on debt.

Barba and Pivetti (2009) concur that living standards tend to determine consumption levels, rather than real wages. Furthermore, workers' consumption is inelastic with respect to the relative reduction in their real wages. This is because the prevailing situation is compounded by the relative stagnation of real wages; as a result, the ratio of desired consumption to income is usually insufficiently high from the households' perspective and therefore reliance on debt becomes the norm.

The other source of debt accumulation across the life-cycle relates to the persistence and intensity of relative consumption concerns. The inter-household imitation indicates an attempt by low to middle-income households keeping up with the consumption lifestyle of the high-income households, which is essentially based on the social visibility of consumption (Barba & Pivetti, 2009). Ravina (2007) also identified a strong empirical presence of inter-household imitation. She found that the level of credit card expenditure is influenced by the consumption patterns of the reference group, who produce Veblen effects.

Based on this account, the elaborate patterns behind consumption expenditure involves, among other factors, the interaction of sets of heterogeneous households through relative consumption and status concerns; an increased living standard, financed through mortgage equity withdrawals; the purchase of the latest consumer goods using credit cards; these are fundamentally contingent on household psychological factors (Cynamon & Fazzari, 2013).

This is contrasted with the representative agent situation that does not allow for interaction but rather an implicit independence between homogeneous agents who do not incorporate sentiments into their consumption behaviour.

3.4 EMPIRICAL LITERATURE REVIEW

In the empirical literature, the focus is on the inevitability of debt's negative effect on consumption, and thus aggregate demand (Barba & Pivetti, 2008; and Cynamon & Fazzari, 2008). The fact that households are required to repay debt would reduce their ability to spend, thus lowering aggregate demand. Kim et al. (2012) calculated a collection of consumption functions to predict the long-term behavior of household debt in the United States. For every percentage rise in debt burden, aggregate consumption was found to be decreased by 0.085 to 0.178 percent.

This, though, is in stark contrast to Schmitt's findings (2000). Schmitt's research focused on Granger-causality tests using economic measures from the United States, such as GDP, on increasing consumer debts in the 1980s and 1990s. She discovered evidence that increased repayment burdens had little effect on consumer spending, leading her to the conclusion that potential responses are not an unavoidable result of unsustainable debt accumulation, but rather that household debt is considered to grow rather than depress economic activity. The problem with these kinds of findings, however, is that indicators of household debt concentration are overlooked.

Households with relatively low incomes, on the other hand, are more likely to hold unskilled job positions that differ cyclically, according to Black and Morgan (1998), so abrupt increases in debt repayment costs result in increased financial hardship for them. According to Murphy (2000), also in the absence of economic shocks, the debt service ratio of households and gross consumption spending on durable goods have a clear inverse relationship. Even if a household's liquidity is limited, discretionary spending decreases as it exceeds a debt level that is unique to them.

From 1994 to 2013, Nkala and Tsegaye (2017) looked at the relationship between household debt and consumption spending. To evaluate the long-run and short-run relationships between the variables, they used the Johansen co-integration technique and the vector error correction model (VECM). The path of causality between the variables was also tested using the Granger causality test. They discovered that in South Africa, there is a connection between household debt and consumption spending; the relationship flows from household debt to consumption spending.

Using extended Kalman filter techniques, Bacchetta and Gerlach (1997) demonstrated that excess sensitivity differs over time and across countries, with a strong downward trend in the United States. Using data from the United States, Canada, the United Kingdom, Japan, and France, they discovered a major impact of credit aggregates on use. Although the borrowing/lending wedge is a major determinant of consumption in the US, Canada, and Japan, it is not in all the countries studied. They said that because consumption is affected by the cost and availability of credit, it plays an important role in the transmission of monetary policy.

According to Ludvigson (1999), as quoted by Johnson and Li (2007), a 0.1 percentage point increase in expected consumer credit growth is associated with a 0.1 percentage point increase in non-durable goods and expenses growth. She also showed how her results could be explained by large differences in consumer credit ceilings. McCarthy (1997) looked at the history of debt in the household sector and consumer spending. The study looked at the associations between debt and spending in aggregate data from the United States over a long period of time (three decades).

Overall, the evidence indicated that a rise in household debt is more likely to be a sign of improved optimism about income prospects than a sign of decreased consumer spending. As cited by Johnson and Li (2007), Jonson (2007) found a marginal correlation between household credit and total expenditures, as well as a negative link between credit-card debt growth and total household expenditures.

To investigate the relationship between household consumption and household debt composition in Malaysia, Khan, Abdullah, and Samsudin (2016) used the Toda – Yamamoto non-causality test. The findings of this study indicate that causality runs from consumption to debt, and the co-integration test results confirm the existence of a long-run relationship between the two variables. The Life Cycle model, which states that a household borrows to fund its consumption and expenses, was also endorsed. Furthermore, their findings indicate that households have been reliant on debt to fund their spending, implying that any negative economic shocks could have significant consequences for the country's economic output.

In 2016, Kim used a multi-equation econometric method to investigate the effect of household debt on GDP in the United States. They discovered a bidirectional positive feedback loop between aggregate income and debt in a vector auto-regression study that captured transitory feed-back effects They discovered a negative relationship between household debt and production using the vector error correction model. In order to capture the short-run and long-run dynamics, Mutezo (2014) used the ARDL-bounds testing procedure to investigate the relationship between household debt and consumption in South Africa from 1986 to 2013.The empirical findings revealed a strong deterministic relationship between household debt and disposable income, net worth, and inflation, but no such relationship existed between debt and the interest rate. In addition, proof of a long-run relationship between household debt and disposable income, interest rate, and inflation was found.

High debt loads are not a bad thing in and of themselves; they can only be considered a concern if the borrowing was focused on unrealistic expectations of future income, He determined that the debt-service ration does not add information to a model of demand growth that includes repressors such as past consumption growth, income growth, wealth growth, and the actual federal funds rate (Maki, 2002). Thus, a quick analysis of the empirical literature on liquidity constraints and use is beneficial. As these are the data that will be used, the emphasis is on studies focused on aggregate data. In addition to demonstrating that excess sensitivity of consumption to income is important for most countries, Bacchetta and Gerlach (1997) investigated three aspects of the liquidity constraint hypothesis:

(i) whether excess sensitivity varies across countries with different financial systems, (ii) whether excess sensitivity in a given country varies over time in response to financial system changes, and (iii) whether financial variables like credit aggregates or interest rates predict consumption.

Regarding the first question, Jappelli and Pagano (1989) showed that the degree of excess sensitivity to income is inversely related to the debt level, thus, countries in which the estimated excess sensitivity to income is low (for instance, Sweden) tend to have the highest consumer debt levels. The authors argue that low debt levels are more likely to come from the supply side (credit rationing), rather than from the demand side.

Using Kalman filtering, McKiernan (1996) discovered that, while excess sensitivity of consumption to income has varied significantly over time in the United States, it has not tended to decline. Turning to the ability of financial variables to predict consumption, there is scattered evidence for individual countries. For the US, using nominal interest rates Mankiw (1982); using prime rates, Wilcox (1989); using the borrowing rate on automobile loans and consumer credit Ludvigson (1996), have been found to be significant.

At this point, it's worth considering the circumstances under which liquidity constraints might become essential. There is likely to be a combination of constrained and unconstrained households in the economy at any given time. However, the relative size of the two classes is likely to vary depending on the state of the country's economy; this may be in relation to individuals who become unemployed with no immediate prospects of finding new jobs. Since banks may be wary of extending loans to fund current consumption in these circumstances, credit market conditions for the unemployed are relatively tight. As a result, the degree to which the household sector is liquidity-constrained is likely to be regarded in these circumstances (Turner, 1997).

3.5 SUMMARY

The reasoning for systematic literature review is based on many principles, one of which is the need to break down vast amounts of knowledge into digestible chunks. The researcher could distinguish insignificant literature from important literature through critical discovery, assessment, and synthesis. This segment delves into the causes of the rapid rise in household consumption in South Africa. Unlike other theoretic models, which consider households as atomistic agents, the approach taken in this study views the household as a fundamental social agent governed by behavioral norms. The effects of household debt accumulation are examined, as well as the dynamics of debt service payments; the emulation boosting impact on consumer credit demand and indebtedness is also considered. However, the evidence to date not only fails to reach a consensus, but it's also difficult to interpret due to the variety of ways debt payments can influence consumption.

CHAPTER 4

RESEARCH METHODOLGY

4.1 INTRODUCTION

In this chapter, the focus is on the discussion of the research paradigm and design, research approach, population, sampling technique, sample size, data collection procedures, data analysis, model specification, diagnostic tests, ethical considerations and summary of study.

4.2 RESEARCH PARADIGM

The paradigm defines a researcher's philosophical orientation and, that has significant implications on every decision made in the research process, including choice of methodology and methods. A paradigm tells us how meaning will be constructed from the data we shall gather, based on our individual experiences, that is, where we are coming from. It is, therefore, very important, that when one writes a research proposal, one clearly states the paradigm in which the study is located (Kivunja & Kuyini, 2017).

Positivism emerged as a philosophical paradigm in the 19th century with Auguste Comte's rejection of metaphysics and his assertion that only scientific knowledge can reveal the truth about reality. The positivist paradigm asserts that real events can be observed empirically and explained with logical analysis (Kaboub, 2008). In this study, positivist paradigm was chosen because it establishes the platform for the researcher to empirically investigate the relationship between consumption expenditure, household disposable income and indebtedness. In order to satisfy the objectives of this study, a quantitative research method was adopted. This is supported by Burns (2000), who argues that quantitative approach is associated with positivist, while qualitative approach is strongly associated with interpretive and critical paradigms. To this end, econometric model based on the Error-correction Model as developed by Davidson *et al.* (1987) was adopted to trace long-run behavior of consumption in South Africa.

4.3 RESEARCH DESIGN

Omari (2011) explains a research design as a distinct plan on how a research problem will be approached. Creswell (2003) and Kerlinger (1978) define research design as the plan, structure and strategy of investigation conceived to obtain answers to research questions and control variance. The research design, thus, is intended to provide an appropriate framework for a study (Aliyu *et al.,* 2014). The reason for using causal design in this study is because the study intends to investigate the relationship between household consumption expenditure, disposable income and indebtedness in South Africa:

4.4 RESEARCH APPROACH

The two main types of research methods are qualitative and quantitative. Quantitative research aligns with the positivist paradigm, whereas qualitative research more closely aligns with the naturalistic paradigm. This study intends to build a quantitative econometric model based on the error correction mechanism first developed by Davidson *et al.* (1987) to trace long run behavior of consumption in South Africa, hence, quantitative approach was adopted. Quantitative approach helps to quantify a problem by way of generating numerical data and transforming them into useable statistics. The study, therefore, was conducted under the auspices of quantitative research approach, so as to tests the existence or lack thereof of a causal relationship among the chosen variables - household consumption expenditure and the relative portion of debt payments to household income. The research used time series data, covering the periods from 1969 quarter 1 to 2019 quarter 4, sourced from Statistics South Africa and South African Reserve Bank. These data are readily available in nominal and real variables.

4.5 SAMPLE, SAMPLING TECHNIQUE AND SAMPLING FRAME

4.5.1 Population of the study

Research population is the group of individuals having one or more characteristics of interest (Asiamah *et al.,* 2017). Welman, Kruger and Mitchell (2005) define population as a study's objects consisting of individuals, groups, organizations, human products and events or the conditions to which they are exposed. The population pertaining to this research were all variables that determine consumption expenditure in South Africa.

4.5.2 Target Population

Target population refers to all the members who meet the criterion specified for a research investigation (Alvi, 2016). The target population of the macroeconomic factors of the study consisted of quarterly data on consumption expenditure, debt service ratio and disposable income. A sample frame is generally thought of as a file from which a sample is selected. The file may be listings that are electronic, paper, file cards, and so on (DiGaetano, 2013).

4.5.3 Sampling Strategy

Alvi ((2016) defines a sample as a group of a relatively smaller number of people selected from a population for investigation purpose; in other words, sampling is the process through which a proportion is extracted from a population (Alvi, 2016). As stated by Alvi (2016), the sampling methods for obtaining representative samples are broadly categorized into major types, which are, probability and non-probability sampling methods. As the study is specifically examining South Africa consumption function, purposive non- probability sampling was used. All the data were of South African origin, as the country is the focus/site of the study. Another reason for using this sampling method is because the study is an exploratory research which is intended to generate new ideas that will be systematically tested later. In addition, the criteria of the elements to include in the study were predefined (Alvi, 2016).

4.5.4 Sample Size

For this study, the period chosen for the econometric analysis was between 1969 quarter 1 and 2019 quarter 4; it is a period of fifty years. A total of 200 observations per series were used in this study starting, from 1969 quarter 1 to 2019 quarter 4 (sample size will be 50 * 4 = 200 observations). These observations are deemed enough to carry out the necessary statistical analyses.

4.6 DATA COLLECTION PROCEDURES

This study used a quantitative data collection method. The data for this study was obtained from the South African Reserve Bank and Statistics South Africa, thus, this study will use secondary time series data. Secondary time series data is defined as recorded data over time, usually at regular intervals (Saunders & Lewis, 2012). This covered the period from 1969 quarter 1 to 2019 quarter 4, which is long enough to capture the long run relationship between the variables. The study will use quarterly data.

4.7 DATA ANALYSIS

The collected data will be entered into Excel**,** a computer program or spreadsheet, before being exported into a software to be used. The study implemented regression analysis to find the impact of debt service ratio and disposable income on consumption expenditure. The study worked with quarterly consumption expenditure data (dependent variable) which was regressed against debt service and disposable income. E- views software was employed to test the validity of the econometric procedures which carried out in this study.

4.8 MODEL SPECIFICATION

The identified model is a three-variable model which hypothesises that consumer expenditure is a function of disposable income and debt-service burden.

$$C = F(YD, DB) \tag{3.1}$$

where C represents household consumption expenditure; YD represents household disposable income and DB represents household debt-service burden. The above-mentioned variables are informed by theory, empirical literature and country-structural characteristics. For example, one of the strands of the empirical literature focused on the existence of liquidity constraints. It was argued that, with binding liquidity constraints, an increase in income, when it occurs, affects consumption. Beside the variable income, according to Bacchetta and Gerlach (1997), it is quite surprising that variables capturing credit conditions are usually not included in empirical consumption function estimations. As such, the above-mentioned equation (7) bodes well for South African household consumer expenditures estimation, given the high rate of unemployment (27.7 %), accompanied by high income inequality (<60%) and compounded by meagre economic growth.

4.8.1 DATA SOURCES AND DEFINITION OF VARIABLES

The quarterly data for the South African economy for the first quarter in 1969 to fourth quarter in 2019 was used for the empirical analysis. Consumption expenditure (C) is represented by final consumption expenditure by households. It was measured at 2010 prices in millions and includes seasonal adjustment. The main concern when modelling the consumption function is which measure of consumption to use. The choice normally falls on either expenditure on non-durable goods and services or total consumption. The former was selected based on the argument that the theory applies to the flow of consumption expenditure, and durable goods are not considered to be part of this flow; this study, therefore, used total consumption. This is because, it allows for more practical forecasts and policymakers usually do not desire to only predict a portion of consumption expenditure. Household income (YD) is represented by disposable income of households in millions measured at 2010 current prices and seasonally adjusted at annual rate. Debt-service burden is represented by ratio debt-service to disposable income measured at current income and seasonally adjusted. The relative debt-service burden is the ratio of regular interest and principal repayments from disposable income. It measures the ongoing burden of the debt on households, as servicing the debt directly affects the current funds available for spending and saving. The compiled dataset was used to develop the Vector Error Correction model in E-views econometric program.

4.8.2 ESTIMATION TECHNIQUES

The empirical analysis stage of the research started by testing for unit roots in the predetermined set of variables, final household consumption expenditure, disposable income and household debt-service burden. A pre-test for stationarity for each of the variables is required to understand the nature of the variables. If a time series is stationary, then its mean, variance, and auto variance (at various lags) remain the same over time, that is, they are time invariant. The thesis employed the following two methods for testing stationarity of the variables.

4.8.2.1 AUGMENTED DICKEY- FULLER (ADF) TEST

The ADF test examines the presence of unit root (non-stationarity) in the autoregressive model. In the case of the Dickey-Fuller test for stationarity, the problem of autocorrelation usually arises and to tackle this problem, the ADF test was developed. The ADF test consists of an estimating the following equation (3.2):

$$\Delta y_t = \beta_1 + \beta_2 t + \delta y_{t-1+\sum_{j=1}^{p} \gamma \Delta y_{t-j} + \varepsilon_t} \tag{3.2}$$

where yt is any time series variable; yt-1 is one period lag value of yt, Δyt = yt – yt-1; and t is the trend variable. The symbols $\beta 1, \beta 2, \delta, and\ \gamma$ are the parameters and εt is a pure white noise error term. The fourth term on the right-hand side of equation 3.2 is the augmentation term. The ADF test is based on the following hypothesis:

Ho: δ = 0 (non-stationary)

H1: δ < 0 (stationary)

The null hypothesis is rejected if the ADF test statistic (tau statistic) is less than its critical value.

4.8.2.2 PHILLIPS- PERRON (PP) TEST

Phillips and Perron proposed a non-parametric statistical method to take care of the serial correlation without an augmented term of the ADF equation (3.2). In this test, the series is assumed to be non-stationary under the null hypothesis. For the PP test, firstly δ is estimated from the non-augmented Dickey-Fuller equation (3.3) as:

$$\Delta y_t \ = \alpha + \beta_t + \delta y_{t-1} \ + \varepsilon_t \tag{3.3}$$

and modifies the $t\delta = \alpha \div se_{\widehat{(\delta)}}$ of the δ coefficient, so that serial correlation does not affect the asymptotic distribution of the test statistics. The PP is based on the following statistic:

$$t_{\delta,pp} = t_{\delta\left(\frac{\gamma 0}{f0}\right)^{\frac{1}{2}}} - \frac{N(f0-\gamma 0)\left(se(\hat{\delta})\right)}{2f_0^{1/2}} \tag{3.4}$$

where $\hat{\delta}$ is the estimated value of δ; t_δ is the ratio of δ; se $(\widehat{\delta})$ is the coefficient standard error, and s is the standard error of the regression. In addition, $\gamma_0$is a consistent estimate of the error variance in a non-augmented Dickey-Fuller (DF) equation (3.3) and calculated as (N – K) s2/N, where K is the number of repressors. The remaining term, f_0 is an estimator of the residual spectrum at frequency zero.

4.8.3 JOHANSEN TEST OF CO-INTEGRATION

This study adopts a dynamic vector autoregressive regression (VAR) which explores co-integration among the chosen time series. VAR models represent statistical descriptions of data series; as such, it is a basis for reducing the model and going into more ordinary structural econometric models, such as Vector Error Correction Model (VECM). In the unrestricted VAR specification, all variables are assumed to be endogenous (there is one equation for each variable), avoiding unnecessary distinctions between endogenous and exogenous variables. The fact that the model does not assume a prior direction of causality among the variables, is particularly useful for the time series, which are often jointly determined, as is the case in this study. This framework is often used to help the formulation of realistic models, uncovering facts and describing the characteristics of the data. The essence is to capture the causal dynamics relationship between consumption, disposable income and debt-service burden, while observing the long- run and short- run dynamics. Estimating VAR is then a way of making sure that the final model is a well-defined statistical model that is consistent with the data chosen (Harris, 1995).

The process, therefore, unfolds with the Johansen co-integration equation which starts with the vector auto regression (VAR) of order p which is given by:

$$Y_t = \mu + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t \qquad \varepsilon_t \sim N_P(0, \Lambda) \qquad (3.5$$

where Y_t is a p-dimensional vector of I(1) of seasonal adjusted variables (consumption expenditure, disposable income and debt-service burden), with t ranging from 1 to T; μ is a vector of constants, and ε_t is a p-dimensional random vector of serially-uncorrelated errors with a variance-covariance matrix Λ. We assume that the system is integrated of order one I, however, if there are signs of I (2) variables, they will be transformed into I (1) before setting the VAR.

In matrix notation, we can express the above VAR as follows:

$$\begin{matrix} C_t \\ YD_t \\ DB_t \end{matrix} = \begin{matrix} c_1 \\ c_2 \\ c_3 \end{matrix} + \begin{matrix} a_{11}^1 & a_{11}^2 & a_{11}^3 \\ a_{21}^1 & a_{22}^2 & a_{23}^3 \\ a_{31}^2 & a_{32}^3 & a_{33}^1 \end{matrix} + \begin{matrix} C_{t-1} \\ YD_{t-1} \\ DB_{t-1} \end{matrix} + \cdots + \begin{matrix} a_{1p}^1 & a_{1p}^2 & a_{1p}^3 \\ a_{2p}^1 & a_{2p}^2 & a_{2p}^3 \\ a_{3p}^1 & a_{3p}^2 & a_{3p}^3 \end{matrix} \times \begin{matrix} C_{t-p} \\ YD_{t-p} \\ DB_{t-p} \end{matrix} + \begin{matrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{matrix} \qquad (3.6)$$

In the VAR model, we need to have the number of appropriate lags. In order to determine the lag length in the VAR model, the Akaike information criterion (AIC) and Schwarz information criterion (SC) were used.

The VAR was transformed to the Vector Error Correction Model (VECM) using the difference operator as follows:

$$\Delta Y_t = \Gamma_1 \Delta Y_{T-1} + \cdots + \Gamma_{k-1} \Delta Y_{t-k-1} + \prod Y_{t-1} + \gamma_0 + \varphi \Delta_t + \varepsilon_t \qquad (3.7)$$

where $\Gamma_i = -(I - A_1 - \cdots A_i), (i = 1, \cdots, k-1),\ and \prod_i = -(I - A_1 - \cdots - A_k)$. This way of specifying the system contains information on both the short- run and the long -run adjustment to changes in Y_t, via the estimates of $\widehat{\Gamma\iota}$ and $\widehat{\prod}$ respectively.

Therefore, the VECM is developed in order to estimate the short -run and long-run association between the variables. As will be seen, $\prod = \alpha\beta'$, where α represents the speed of adjustment to disequilibrium, while β' is a matrix of the long-run coefficients, such that, the term $\beta' Y_{t-k}$ embedded in (3.7) represents up to (n-1) co-integration relationships in the multivariate model, which ensure that the Y_t converge to their long-run steady state solutions (Harris, 1995).

Determining the number of co-integrating vectors requires knowledge about the position or rank (r) of the matrix$\prod$. The rank of matrix $\prod$ determines the number of cointegrating as well as the number of independent variables. The rank is given by significant eigenvalues found in $\prod$ where each stand for a significant stationary relation. According to Davidson (1995), there are three possibilities:

(i) The position of $\prod$ being complete. In this situation, any linear combination between the variables is stationary, and the model adjustment shall be made with the variables in the level.

(ii) The position of $\prod$ being null, there is no cointegration relationship and the model must adjust with the variables indifferences.

(iii) The matrix $\prod$ having a reduced position. In this case, there are r cointegrating vectors, in which 0 < r < n

The number of co-integration relationship (r) is determined by the Johansen maximum likelihood-based method. Trace tests and maximum Eigenvalue tests were used here to determine the number of co-integrating equations between the concerned variables. The trace test seeks to test the null hypothesis; that the number of distinct co-integrating vectors is less than or equal to r (H_0 = cointegrating vectors ≤ r), against the alternative hypothesis that the number of these vectors is greater than r (H_1 = cointegrating vectors > r). The trace test can be expressed as follows:

$$\lambda_{trace}(r) = -T\sum_{1=r+1}^{n} \ln{(1-\lambda i)} \qquad (3.8)$$

where λ_i are the estimated values of the characteristic roots obtained from the Π and T matrix is the number of observations?

The maximum eigenvalue test aims to test the null hypothesis, that the number of vectors is r (H_0: co-integrating vectors =r) against the alternative hypothesis of the existence of r + 1 co-integrating vectors (H_1: co-integrating vectors = r + 1). The maximum eigenvalue test can be represented as follows:

$$\lambda_{\max{(r,r+1)}} = -Tln(1-\lambda_{r+1}) \qquad (3.9)$$

In case there is a conflict between the two tests, the maximum eigenvalue test is preferred. The maximum eigenvalue test is said to have a sharper alternative hypothesis, and as such, it is usually preferred for trying to pin down the number of co-integrating vectors (Hafer & Jansen, 1991).

4.8.4 WEAK EXOGENEITY

A central assumption behind building a single equation ECM is weak exogeneity. This is related to which variable adjusts to maintain the long - run relationship. An estimation of the conditional consumption function implicitly assumes that consumption is the only variable that equilibrium corrects. We can test this assumption by testing if the coefficients in the α-vector, related to the other variables, also called the “loadings”, are significantly different from zero. The way we do this is to restrict these variables to zero when doing an analysis of the relevant co-integrated VAR, and then doing a likelihood-ratio test on the restrictions. If the restrictions pass the test, then we have statistical support for estimating the conditional consumption function (Bardsen & Nymoen, 2014, as cited in Landsem, 2016).

4.8.5 VECTOR ERROR CORRECTION MODEL (VECM)

If co-integration is detected between series, we know that there exists a long-term equilibrium relationship between them; so, we apply VECM in order to evaluate the short run properties of the co-integrated series. In case of no co-integration, VECM is no longer required, and we directly precede to the Granger causality tests to establish causal links between variables (Engle & Granger,1987).

The advantage of using vector error correction (VECM) modelling framework in testing for causality is that, it allows for the testing of short-run causality through the lagged differenced explanatory variables and for long-run causality through the lagged error correction term (ECM). A statistically significant term represents the long-run causality running from the explanatory variables to the dependent variable. Furthermore, VECM is useful when a long-run forecast is desired, as VAR does not explicitly consider the long-run relationship (Engle & Granger,1987).

Engle and Granger (1987) demonstrate that once a number of variables (say, Y, YD and DB) are found to be co-integrated, there always exists a corresponding error-correction representation that implies that changes in the dependent variable are a function of the level of disequilibrium in the co-integrating relationship (captured by the error-correction term) as well as changes in the other explanatory variables (Masih & Masih, 1997). If we exploit the idea that there may exist movements between consumption (C_t), disposable income (YD_t) and debt-service burden (DB_t) of South Africa, and the possibilities that they will trend together in finding a long-run stable equilibrium, through the Granger representation theorem, we may posit the following testing relationships, which constitute our vector error-correction model:

$$\Delta C_t = \alpha_1 + \sum_{i=1}^{l} \beta_{1i} \Delta YD_{t-1} + \sum_{i=1}^{m} \gamma_{1i} \Delta C_{t-1} + \sum_{i=1}^{n} \delta_{1i} \Delta\, DB_{t-1} + \sum_{1=i}^{r} \xi_{1i} ECT_{r,t-1} + \mu_{1t}$$

(3.10)

$$\Delta YD_t = \alpha_2 + \sum_{i=1}^{l} \beta_{2i} \Delta\, YD_{t-1} + \sum_{i=1}^{m} \gamma_{2i} \Delta C_{t-1} + \sum_{i=1}^{n} \delta_{2i} \Delta DB_{t-1} + \sum_{i=1}^{r} \xi_{2i} ECT_{r,r-1} + \mu_{2t}$$

(3.11)

$$\Delta DB_t = \alpha_3 + \sum_{i=1}^{l} \beta_{3i} \Delta YD_{t-1} + \sum_{i=1}^{m} \gamma_{3i} \Delta C_{t-1} + \sum_{i=1}^{n} \delta_{3i} \Delta DB_{t-1} + \sum_{i=1}^{r} \xi_{3i} \Delta ECT_{r,t-1} + \mu_{3t} \quad (3.12)$$

where [C_t, YD_t, DB_t] are household consumption expenditure, disposable income and debt-service burden, respectively; Δ is the difference operator, ECT refers to the error-correction terms derived from long-run co-integrating relationship via the Johansen maximum likelihood procedure and $u_{i,t}$'s (for I = 1,2,3) are serially uncorrelated random error terms with a mean of zero.

In this study, equation (3.10) was used to test causation from disposable income and debt-service burden in relation to consumption expenditure. Equation (3.11) was used to test causality from consumption and debt-service burden to disposable income. Equation (3.12) was used to test causality from consumption and disposable income to debt-service burden. A consequence of relationships, described by equations 3.10 to 3.12, is that either ΔYD_t, ΔC_t, ΔDB_t or a combination of any of them must be caused by ECT_{t-1}, which is itself a function of YD_{t-1}, C_{t-1}, and DB_{t-1}. Through the ECT, the ECM opens an additional channel for the Granger test. The Granger causality (or endogeneity of the dependent variable) can be exposed either through the statistical significance of lagged error terms (ξ's) by a t test as well as a joint test applied to the significance of the lags of each explanatory variable by joint F or Wald χ^2 test.

In addition, to indicating the direction of causality amongst variables, the VECM approach allows us to distinguish between short-run and long-run Granger causality. When the variables are co-integrated, then in the short term, deviations from this long-run equilibrium will feed back on the changes in the dependent variable, in order to force a movement towards the long-run equilibrium. If the dependent variable is driven directly by this long-run equilibrium error, then it is responding to this feedback; if not, it is responding only to short-term shocks in the stochastic environment. The F-tests of the differenced explanatory variables give us an indication of the short-term causal effects, whereas the long-run causal relationship is implied through the significance or otherwise of the t-tests of the lagged error terms that contain the long-term information, since it is derived from the long-run co-integrating relationships. The coefficient of the lagged error-correction term, however, is a short-term adjustment coefficient and represents the proportion by which the long-run disequilibrium in the dependent variable is being corrected in each short period (Masih & Masih, 1997).

4.8.6 IMPULSE RESPONSE FUNCTION (IRF) AND FORECAST ERROR VARIANCE DECOMPOSITION

Once we have decided the final VECM model, its estimated parameter values have to be interpreted. Since in such a model all variables depend on each other, individual parameter values only provide limited information. In order to get a better intuition of the model's dynamic behaviour, impulse responses are used. They give the reaction of a response variable to a one-time shock in an impulse variable. In addition, the trajectory of the response variable can be plotted, which results in those wavy curves seen in many macroeconomics papers. Due to the difficulty of interpreting the estimated coefficients for the VAR model, it is common to summarize the results by means of the impulse-response function and of the variance decomposition (da Silva, 2014). Once the VECM has been estimated, short-run dynamics can be examined by considering the impulse response function and variance decomposition. This study also used the impulse response function and variance decomposition as additional checks on the co-integration test's findings (da Silva, 2014).

Dynamic in-sample simulation and deterministic analysis of the response characteristics of the model, which test, whether short and long-run response characteristics correspond to theoretical priors and long-run equilibrium properties of the data, often prove helpful in assessing the validity of the model. The process would consist of conducting a dynamic baseline forecast for each stochastic equation. An exogenous shock is applied to the system and the adjustment path towards a new equilibrium is then determined. Dynamic out-of-sample simulation can be used in establishing the forecasting performance of the model (da Silva, 2014).

4.8.6.1 IMPULSE RESPONSE FUNCTION

The stochastic error terms are called impulses or innovations in the language of VAR. Impulse response traces out the response of current and future values of each of the variables to a one-unit increase in the current value of one VAR errors, if this error returns to zero in subsequent periods, then all other errors are equal to zero. In other words, it outlines the behaviour of the series included in the VAR model in response to shocks caused by residual variables.

Any covariance stationary VAR (p) process has a Wold representation (vector MA ∞(moving average) process) of the following form:

$C_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \Psi_3 \varepsilon_{t-3} + \cdots$ (3.13)

Thus, the matrix ψ_s has the interpretation

$$\frac{\partial Y_{T+S}}{\partial \varepsilon_t'} = \Psi_s$$

that is, the row I, column j element of ψ_s identifies the consequences of a one-unit increase in the jth variable's innovation at date t (ε_{jt}) for the value of the ith variable at time t + s($y_{i,t+s}$), holding all other innovations, at all dates constants. A plot of the row I, column j element of ψ as a function of s is called the "impulse response function".(Llu & Xin, 2010).

4.8.6.2 VARIANCE DECOMPOSITION

A VDC technique focuses on the dynamics of series, due to innovative shocks stemming from other series along with its own shock and reflecting whether the series has strongly impacted each other over the time periods. In this way, the use of VDC analysis could be more beneficial for researchers, to isolate the relative dynamic effects of its own shock and innovative shocks stemming from other independent variables towards dependent variables of the estimation process

Forecast error can be obtained from the variance decomposition of each VAR model. The hth step forecast error and its variance can be computed, respectively, as:

$Y_{t+h} - E(Y_{t+h} = \Psi_0 \varepsilon_{t+h} + \Psi_1 \varepsilon_{t+h-1} + \cdots + \Psi_{h-1} \varepsilon_{t+1}$ (3.14)

and

$\text{var}_t(Y_{t+h)} = \Psi_0 \Psi_0' + \Psi_1 \Psi_1' + \cdots + \Psi_{h-1} \Psi_{h-1}'$ (3.15)

$w_{h,r} = \sum_{j=1}^{h-1} \Psi_j I_N \Psi_j'$ is the variance of h step ahead forecast errors due to the Nth shock and the variance is the sum of these components, for example, $\text{var}_t(Y_{t+h}) = \sum_N w_{h,r.}$ (Masih & Masih, 1998)

4.9 DIAGNOSTIC TESTS

To ensure the goodness of fit of the model, diagnostic tests will be conducted. Diagnostic checking is, therefore, a very important part of the whole process of model selection. In order to assess the validity of the model, it must be subjected to a battery of diagnostic tests. Tests developed to test for constancy of parameter vector were examined using a Chow test; autocorrelation and heteroscedasticity was examined through several tests, namely, the Lagrange multiplier test and Box-Pierce test, among others; the Breusch-Pagan test for heteroscedasticity and the normality assumption was tested by the Jaeque-Bera test.

4.10 ETHICAL CONSIDERATIONS

Research does not always involve the collection of data from participants. The existing data such as time series data is freely available from the Reserve Bank and Statistics South Africa and can be analysed to answer critical research questions (Tripathy, 2013). These data have no identifying information.

In this dissertation, secondary data in the form of time series data, starting from quarter 1 1969 to fourth quarter 2019, were used to carry out an econometric evaluation of the consumption function of South Africa. These data were sourced from South African Reserve Bank and Statistics South Africa. These types of data were downloaded from the abovementioned sources, as they are readily available for public consumption and are completely devoid of identifying information. It is ethically important that a valid interpretation is presented of the results of the study, as misleading conclusions can falsely influence practice and further research. The researcher will try his best to present the findings and interpretations honestly and objectively, by using the available statistical checklists. Finally, potential users of the results will be forewarned about the limitations and assumptions underpinning the research.

4.11 SUMMARY

The research process involves the application of various methods and techniques to create a scientifically credible knowledge. A positivist paradigm was selected for this quantitative research study. This paradigm helps a researcher to clearly understand the objectives by empirical tests and methods, such as sampling and questionnaire. The research study will adopt a causal design, which is suitable for a quantitative research approach. The research identified households as the target population and purposive sampling was identified as the suitable sampling techniques. To this end, this research seeks to model the impact of household indebtedness on consumption expenditure, using Vector Error-Correction econometric modelling.

CHAPTER 5

DATA ANAYSIS, RESULTS AND DISCUSSIONS

5.1 INTRODUCTION

This chapter serves as a summary of the entire study, presenting the findings, problems faced, and potential future research opportunities in a variety of ways.

5.2 DATA AND TIME SERIES DESCRIPTIONS

For the analysis of the relationship between consumer expenditure, disposable income and debt-service ratio in South Africa from quarter 1 1969 to fourth 2019 period, the following behaviourial function was adopted.

$$C = (YD, DB)$$

C = Total Private Consumption Expenditure

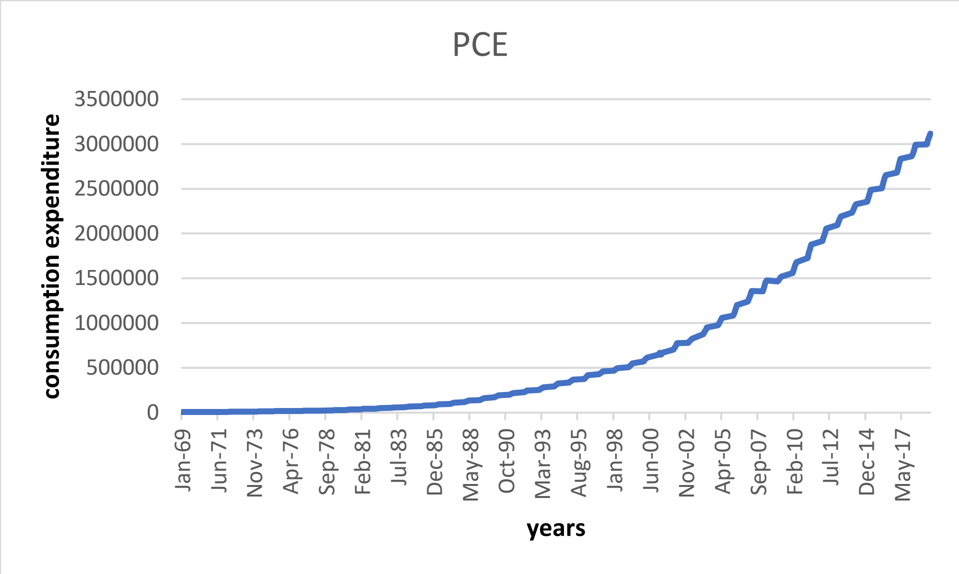
YD = Disposable income

DB = Debt Service Ratio

The quarterly data of the South African economy for the period from 1969 to 2019 was used in the estimation. The data used is sourced from the South African Reserve Bank to develop a relevant trivariate Vector Error Correction model in E-views 12 econometric program. All variables are seasonal adjusted and expressed in log form.

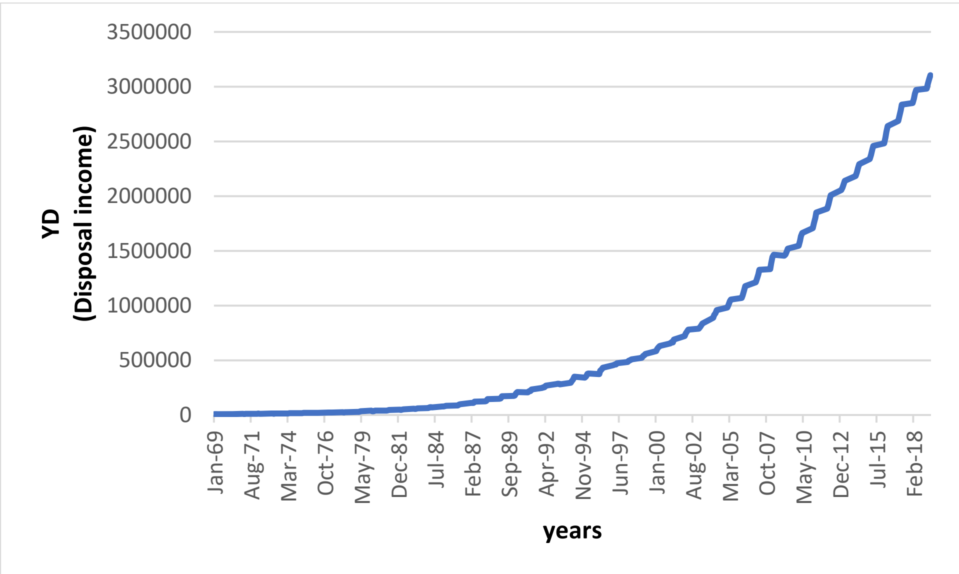
Total personal consumption expenditure was used to measure consumer spending at constant 2010 price. Personal disposable income was used as the source of household income adjusted for income tax. The debt-service ratio, which is the ratio of household debt service to personal disposable income, was used to measure the debt burden (Murphy, 1988).

The graphically representation of the chosen time series data can be very useful to the researcher as a prelude to the presentation of the results. While it is not a confirmatory study, it does make a significant difference in terms of the underlying pattern of the series in question. Both consumer expenditure and disposable income are on the rise, though there are some fluctuations. The consumption expenditure as well as disposable income show a marked increase around 2002. Furthermore, consumption expenditure and disposable income trend together. The debt-service ratio also shows rising but subject to rigorous fluctuations at times. The debt-service ratio reached high peak during the period 2000 to 2001.



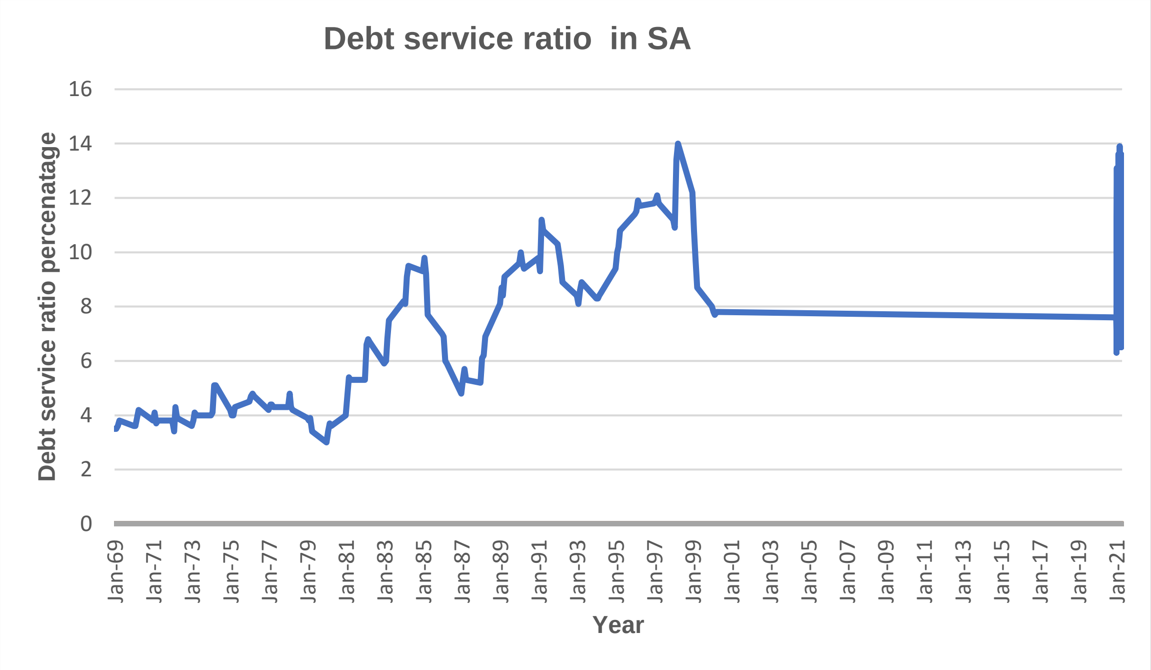
Data source: SARB (2019)

Figure 5.1: Household consumption expenditure trend in South Africa



Data source: SARB (2019)

Figure 5.2 Household disposable income trend in South Africa



Data source: SARB (2019)

Figure 5.3 Household debt-service ratio trend in South Africa

5.3 RESULTS OF UNIT ROOT TESTS

Unit root tests are used because most macroeconomic time series data are non-stationary, and stationarity is a requirement for variables to co-integrate.

The Augmented Dickey Fuller (ADF) and Phillips and Perron (PP) (1988) procedures were used to check for stationarity for all variables. Tables 5.1 show the effects of the ADF and PP analyses respectively.

Consumption spending, disposable income, and debt-service ratio are non-stationary processes according to the ADF tests (p-value>0.05) in Table 5.1, but after first differencing, all variables become stationary and all variables are integrated of order one, that is, I. (1).

The PP tests show that consumption spending and disposable income are non-stationary processes (p-value>0.05), but the debt-service ratio is stationary at its current level (see Table 5.1). However, after first differencing, consumption expenditure and disposable income become stationary, implying that they are integrated of order one, i.e. (1).

For the variable debt-service ratio, the results of the ADF and PP tests differ; however, this does not pose a problem because when you have three series, two of which are integrated of order one and the other of which is integrated of order zero, they can still co-integrate; this would happen if the two integrated of order one co-integrate.

Table 5.1. Unit Root Based on Augmented Dickey Fuller (ADF) Test

ADF Test Statistics

Variables	Intercept	P-value	Intercept and Trend	P-value
LC	-3.5724	0.0071	2.7839	1.0000
LYD	-5.3729	0.0000	1.6055	1.0000
LDB	-4.4753	0.0000	-5.5018	0.0000
ΔLC	-4.0225	0.0016	-5.6139	0.0000
ΔLYD	-3.2134	0.0207	-13.8591	0.0000
ΔLDB	-26.4390	0.0000	-34.9251	0.0001

Table 5.1. Unit Root Based on Philips-Perron (PP) Test

PP Test Statistics

Variables	Intercept	P-value	Intercept and Trend	P-value
LC	-4.3199	0.0005	1.6639	1.0000
LYD	-3.1979	0.0215	0.5664	0.9994
LDB	-4.4753	0.0000	-5.5018	0.0000
ΔLC	-11.8304	0.0000	-13.0013	0.0000
ΔLYD	-19.8316	0.0000	-23.0398	0.0000
ΔLDB	-26.4390	0.0000	-34.9251	0.0001

5.4 THE JOHANSEN COINTEGRATION TEST RESULTS

An unrestricted tri-variate VAR model with all variables in levels is calculated to look for a co-integrating relationship between the three variables. The optimal lag period in the VAR model must be calculated before the co-integration test can be used. The majority rule among information criteria (AIC and FPE) suggests that a lag length of 6 is appropriate (Table 5.2).

Table 5.2. Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-163.212	NA	0.0011	1.6961	1.7462	1.7164
1	959.9972*	2004.67	3.50E-08	-8.6530	-8.4523*	-8.5718*
2	866.0143	11.6043	3.61E-08	-8.6225	-8.2714	-8.4804
3	878.6993	24.0756	3.48E-08	-8.6787	-8.1584	-8.4571
4	889.5098	20.1870	3.42E-08	-8.7659	-8.0264	-8.4146
5	907.0588	32.2328	3.13E-08	-8.7659	-7.9631	-8.4409
6	920.0083	23.3886	3.01E-08*	-8.8062*	-7.8529	-8.4203
7	927.8069	13.8465	3.05E-08	-8.7940	-7.6901	-8.3471
8	933.7777	10.4183*	3.15E-08	-8.7630	-7.5087	-8.2552

The co-integrating rank is calculated using Johansen (1998) methodology, which yields two probability estimators: a trace test and a maximum eigenvalue test. The null hypothesis for both the trace and maximum eigenvalue tests was that no co-integrating relationships exist, with the alternative hypothesis for the trace test being that there are more than zero relationships, and the alternative hypothesis for the maximum eigenvalue test being that there is at least one co-integrating equation.

The test statistics are compared with the critical values and if the calculated statistics are higher than the test critical values, the null hypothesis is rejected. The trace test statistic of 98.2404 is greater than the critical value of 35.0109, indicating that the null hypothesis of no co-integration is rejected and that there are more than zero relationships, as shown in Table 5. 3. This is confirmed by the maximum-eigenvalue test statistic, which shows that the estimated statistic of 52.237 is greater than the critical value of 24.2520, indicating that there is evidence of cointegration (Table 5.3)

For the trace test and at least two for the maximum-eigenvalue test, a second test was conducted with the null hypothesis of one co-integrating relationship versus the alternative of more than one relationship.

The results of the trace test showed that the test statistic of 46.0026 is greater than the critical value of 18.3977. The maximum eigenvalue test statistic of 42.7704 exceeds the critical value of 17.1477. As a result, the null hypothesis of at most one co-integrating equation was found to be false (Table 5.3).

The null hypothesis of two co-integrating vectors was used in the third test since these were evaluated in order. The trace test figure of 3.2322 is less than the critical value of 3.8414 in the results below (marginal). 3.2322 is less than the critical value of 3.8415 in the maximum eigenvalue test statistic (marginal) (Table 5.3). Since the series are co-integrated, the results of the co-integrating tests show that the VECM, rather than a VAR, is the best strategy for modeling the relationship between HCE(C), HDI (YD), and DSR) DB). The Granger Representation Theorem, which states that two or more integrated time series that are co-integrated have an error correction representation, is the relation between co-integration and error correction models (Engle & Granger, 1987).

Table 5.3 Cointegration Tests

Unrestricted Co-integration Rank Test: Trace Statistics

Hypothesized No. of Co-integrations.	Eigenvalue	Trace Statistics	0.05 Critical Value	Probability
None (H_0 : r = o, H_1 : r = 1)	0.2059	89.0434	29.7970	0.0000
At most 1 (H_0 : r = 1, H_1 : r = 2)	0.1238	42.6877	15.4947	0.0000
At most 2 (H_0: r = 2, H_1 : r = 3)	0.0770	16.1089	3.8414	0.0001

Unrestricted Co-integration Rank Test: Maximum Eigenvalue Statistics

Hypothesized No. of Co-integrations.	Eigenvalue	Maximum Eig.	0.05 Critical Value.	Probability
None (H_0: r = 0, H_1: r = 1)	0.20596	46.3557	21.1316	0.000
At most 1 (H_0: r = 1, H_1: r = 2)	0.1238	26.5787	14.2646	0.0004
At most 2 (H_0: r = 2, H_1: r = 3)	0.0770	16.1089	3.8414	0.0001

The trace and maximum eigenvalue statistics for determining the number of co-integrating vectors (r) using Johansen's maximum likelihood approach are stated in tables 5.3 above.

5.5 VECTOR ERROR CORRECTION MODEL (VECM)

5.5.1 ANALYSIS OF THE LONG-RUN RELATIONSHIP

The results of both the trace and maximum-eigenvalue tests reveal three co-integrating equations, meaning that there are long-run relationships between household spending expenditure, disposable income, and debt-service ratio.

$$LC = -0.3006 + 1.0195LYD + 0.0066LDB$$

As shown by the co-integrating equation above, the long-run coefficients of household disposable income and household debt-service ratio are both positive. This means that disposable income and the debt-service ratio have a positive long-term effect on household consumption spending. The marginal propensity to consume is 1.0195, implying that a 1% rise in disposable income induces a 1.0195 percent increase in household consumption expenditure in the long run. Household spending expenditure rises by 0.0066 percent as the debt-service ratio rises.

In this analysis, the substantial long-run impact of disposable income on household consumption expenditure supports the relative income hypothesis that household income has a long-term effect on household consumption expenditure. This finding is consistent to that of Osei Bonsu and Muzindutsi's research (2017).

The importance of a long-run positive relationship between debt-service ratio and household consumption expenditure is that understanding long-run aggregate consumption expenditure behavior requires understanding household debt (Moura, 2014).

5.5.2 SHORT-RUN RELATIONSHIPS

The short-run change to equilibrium was calculated using the VECM. If the variables have a co-integrating relationship, the error correction must be negative and meaningful, according to the theoretical basis of the error correction model.

Only household consumption expenditure has the desired negative sign and is meaningful, according to the error-correction results in Table 5.4 below from the VECM. This means that the household consumption expenditure equation explains how long-run shocks impact equilibrium and how they are adjusted.

According to the error-correction coefficient, about 2% of the variance from equilibrium is removed each year. Changes in independent variables take about 50 years (1/0.0200) to have a maximum impact on household consumption spending, according to the findings.

Table 5.4. Error Corrections Results

Variables	D(LC)	D(LYD)	D(LDB)
ECT Coefficients	-0.0200	0.6880	1.8991
Standard Errors	0.0458	0,1160	1.2858
T-Value	-0.4361	5.9296	1.4708

5.6 GRANGER CAUSALITY TESTS

While co-integration between variables specifies the direction of any causal relationship, economic theory guarantees that there is always Granger Causality in at least one direction (Fizari, et al., 2011). Table 5.5 shows the estimation results for Granger Causality between the LC, YD, and DB. The null hypothesis is rejected when the likelihood values are important.

Table 5.5. Pairwise Granger Causality Test

Null Hypothesis	F-statistic	Probability	Decision
LC does not Granger Cause LYD	2.5795	0.0201	Do not reject
LYD does not Granger Cause LC	7.1901	7.E-07	Reject
LDB does not Granger Cause LC	0.5834	0.7432	Do not reject
LC does not Granger Cause LDB	1.9918	0.0689	Do not reject
LDB does not Granger Cause LYD	1.4320	0.2044	Do not reject
LYD does not Granger Cause LDB	1.7459	0.1126	Do not reject

Due to the complexity of interpreting the estimated coefficients for the VAR model, the impulse-response function and variance decomposition are commonly used to summarize the results (da Silva, et al., 2014)

5.7 IMPULSE RESPONSE ANALYSIS

Impulse-response analysis was developed from the VECM to further investigate the short-run relationships between household consumption expenditure and the selected time series variables. It's used as a secondary check on the results of the co-integrating tests. To draw a meaningful interpretation, the Cholesky of contemporaneous identifying constraints is used, and the recursive structure implies that variables occurring first affect later variables contemporaneously, but not vice versa (Fizari, et al., 2011).

The initial response of consumption expenditure to a unit shock in household disposable income is positive and rises gradually, as shown by the impulse-response functions in Table 5.6. The response of household consumption expenditure to a unit shock in the debt-service ratio is negative and gradually diminishes.

Table 5.6: Impulse Response Function

Period	LPCE	LHDI	LDSR
1	0.014023	0.000000	0.000000
2	0.016562	0.001147	0.000780
3	0.020110	0.001778	0.001758
4	0.021485	0.001195	0.003620
5	0.022918	0.000944	0.005362
6	0.024057	0.000698	0.006986
7	0.025101	0.000166	0.008520
8	0.026057	-0.000364	0.009994
9	0.026976	-0.000820	0.011371
10	0.027840	-0.001286	0.012644

When a unit shock in household consumption expenditure occurs, the initial response of household disposable income is positive. Debt-service ratio is neutral in the response of household disposable income to a unit shock in household. The initial reaction of the household debt-service ratio to a unit shock in household consumption expenditure is positive, with the ratio rising initially before leveling off. The initial reaction of the household debt-service ratio to a unit shock in disposable income is negative, and it gradually fades away.

5.8 VARIANCE DECOMPOSITION ANALYSIS

Consumption expenditure was subjected to variance decomposition in order to see whether an increase in household disposable income would result in an increase in consumption expenditure. Additionally, a debt-service ratio variance decomposition was performed to identify significant variables that explain variation in the debt-service ratio.

Changes in household consumption expenditure in the first year can be explained entirely by changes in household consumption expenditure. After ten years, household disposable income explains 1.6 percent of shifts in consumer spending, while household debt-service ratio explains just 0.7 percent.

This indicates that household consumption spending is primarily influenced by shocks that occur within the household. This finding appears to support Duesenberry's (1949) hypothesis that consumption is influenced by previous levels of consumption (Osei Bonsu & Muzindutsi, 2017)

Table 5.7 Variance Decomposition of Household Consumption Expenditure

Period	S.E	LC	LYD	LDB
1	0.0137	100	0	0
2	0.0206	99.3965	0.4866	0.1169
3	0.0274	99.6794	1.0318	0.4449
4	0.0331	98.4405	1.1146	0.4450
5	0.0381	98.2456	1.2162	0.5382
6	0.0426	98.0423	1.3573	0.6003
7	0.0468	97.7708	1.4630	0.6507
8	0.0505	97.7708	i.5414	0.6877
9	0.0540	97.6766	1.6101	0.7133
10	0.0573	97.5993	1.6101	0.732

5.9 VECM DIAGNOSTIC TESTS

The statistical properties of the model must be investigated in order for the findings to be econometrically credible (Sing, 2004). The robustness of calculated coefficients is determined by diagnostic tests. The type of diagnostic tests used depends on the modeling methodology used; however, coefficient diagnostics and residual diagnostics are the most common types of diagnostic tests.

Since regression models aim to eliminate errors (or residuals), residual diagnostics is the most important part of diagnostic tests in economic modeling. It has to be white noise as an error expression (independently and identically distributed, i.i.d .The residual diagnostics look at whether the error terms are i.i.d., while the stability diagnostics look at whether the calculated model's parameters are stable across different sub-samples of data (Shrestha & Bhatta, 2018).

Autocorrelation, heteroscedasticity, and normality tests were performed on the model. The Breusch-Godfrey test was used to see whether there were any serial similarities. The White test was used to check for heteroscedasticity, and the Jargue-Bera LM test was used to check for normality.

5.9.1 TEST FOR AUTOCORRELATION

Table 5.8 Autocorrelation (LM)

Lag	Rao F-stat	DF	PROB>CHI2
1	3.0476	9	0.0015
2	5.0148	9	0.0000
3	2.2916	9	0.0160
4	2.9505	9	0.0020

H_O: No Autocorrelation at lag 1 to 4

We can't rule out the null of residual autocorrelation at orders 1 to 4, because the F-statistics are significant (p-value < 0.05), but there's no need to doubt VAR's validity. When estimating time series, the absence of autocorrelation is crucial since a model with autocorrelation in the residuals will not yield consistent results. It is important to eliminate autocorrelation by adding more lags. The presence of autocorrelation might be indicative of the fact that the model is misspecified.

5.9.2 HETEROSKEDASTICITY TEST
Joint test

Chi2	Df	PRO
175.8303	96	0.0000

The results show a large Chi2 of 175.8303. A model with a large chi2 indicates a mis-specified model. There is a fair chance that certain crucial variables were left out in order to create a parsimonious model. Variables like unemployment rate and income distribution may influence the aggregate consumption expenditure given South African economic landscape

5.9.2 NORMALITY TEST

In order to make inferences in the model, the residual must be normally distributed. The mean and variance are the only two moments in a naturally distributed distribution. The Jaeque-Bera test is the most widely used normality test (Sjo, 2012).

Joint test: Jaeque-Bera test

Joint	DF	PROB
437.3417	6	0.0000

The fact that the Jaeque-Bera p-value is less than 0.05 indicates that the residual is not normally distributed.

5.11 SUMMARY

The findings of this study show a positive relationship between consumption and expenditure, which is consistent with consumption function theories. The findings of a positive relationship between consumption expenditure and debt service ratio, on the other hand, are hotly debated among various economic schools of thinking. The error-correction coefficient is quite small (0.0200); indicating the fact that it takes quite a long time for the adjustment back to equilibrium after a shock. The adjustment is carried by consumption expenditure. The tact that the debt-service series is stationary rules it out of play any role adjustment to equilibrium after experiencing a shock. The findings show that the model is stable with AR roots within the unit circle or less than one.

CHAPTER 6

SUMMARY, FINDINGS, POLICY RECOMMENDATIONS, LIMITATIONS AND FUTURE RESEARCH.

6.1 INTRODUCTION

In this chapter, the summary of the research is outlined, and policy recommendations will be presented. The limitations of the research as well as suggestions for future research will be presented.

6.2 SUMMARY OF THE STUDY AND FINDINGS

In the form of the relative income hypothesis, the study's main goal was to assess the relationship between household consumption expenditure, household disposable income, and household debt-service ratio. The study's introduction and context were discussed in the first chapter, which resulted in the formulation of the problem statement. Following that, the study's research questions, goals, hypotheses, and structure were created. In Chapters 2 and 3, both theoretical and empirical literature is reviewed and presented to provide the research with a context. The vector error correction approach and its modalities were discussed in Chapter 4, and the empirical research was covered in Chapter 5. The summary, conclusion and policy recommendation among others are covered in Chapter 6.

The research attempted to estimate consumption for South Africa using vector error-correction modelling. The aim of the research was to investigate the connection between household consumption expenditure and debt burden as measured by the debt-service ratio. It was discovered in this study that consumption expenditure is sensitive to household disposable income, this is shown by marginal propensity to consume of 1. According to the study's findings, household debt, as measured by the debt-service ratio, has a positive influence on consumption expenditure, albeit small. The study found out that consumption adjusts to equilibrium levels quite slow. The findings of this analysis are more in line with a Keynesian viewpoint supplemented by the theory of relative income hypothesis. Given the non-stationary nature of the variables, the vector error correction framework was appropriate.

6.3 POLICY RECOMMENDATIONS

Based on the findings of study, the following recommendations are proposed:

- In South Africa, disposable income was found to have a positive impact on household consumption spending. As a result, the study suggests that the South African government consider implementing a basic income grant to help relieve the effects of high unemployment and poverty. Given that most people invest a substantial portion of their discretionary income on consumption, the government's revenue in the form of taxation would help to alleviate the fiscal burden.
- The study discovered that consumption expenditure and household income, as well as household debt burden, have a positive relationship. To have a clear understanding of the impact of monetary policy, the government should strive to have a working knowledge of the determinants of household income. When credit constraints are time-varying, credit, according to Bacchetta (1997), matters specifically. Since consumer preferences are complex and changes in a country's socioeconomic structure affect household consumption, the estimation of the time-varying liquidity constraint model is very revealing.

6.4 LIMITATIONS

The presented findings have some flaws, including the lack of variables such as household income and debt distribution. Higher income inequality, according to the relative income hypothesis (1949), can force households to borrow in order to maintain their consumption standards in comparison to their reference group (Mourad, 2014). This necessitates a precise representation of the consumption function and the resulting dynamics; however, the absence of certain variables, such as income distribution and household wealth, which result in a model that is incorrectly defined.

.6.5 FUTURE RESEARCH

This research is conducted from a macroeconomic standpoint; however, in order to fully comprehend the consumption mechanism, a microeconomic approach that considers debt distribution across classes would be beneficial to the subject. In the future, research on the determinants of consumption spending should attempt to include as many variables as possible, such as income distribution and household size, in order to capture a more accurate image of the situation, while keeping model parsimony in mind.

6.6 SUMMARY

Overall, the study's results show that in South Africa, there is a long-run relationship between consumption spending, disposable income, and debt burden, as measured by the debt-service ratio. The marginal propensity to spend is 100 percent, and the disposable income coefficient is positive and important. According to Hossain and Chowdhury (1998), "one explanation why current income is closely associated with consumption expenditure is the high incidence of absolute poverty," which is exacerbated by the existence of liquidity constraints.

REFERENCES

Alimi, R. Santos, 2013. "Keynes' Absolute Income Hypothesis and Kuznets Paradox," MPRA Paper 49310, University Library of Munich, Germany.

Aliyu, A. A., Bello, M. U., Kasim, R., & Martin, D. (2014). Positivist and non-positivist paradigm in social science research: Conflicting paradigms or perfect partners. *J. Mgmt. & Sustainability*, *4*, 79.

Alvi, M. (2016). A manual for selecting sampling techniques in research.

Asari, F. F. A. H., Baharuddin, N. S., Juso, N., Mohamad, Z., Shamsudin, N. & K. Jusoff (2011). 'A Vector Error Correction Model (VECM) Approach in Explaining the Relationship between Interest Rate and Inflation towards Exchange Rate Volatility in Malaysia'. *World Applied Sciences Journal*, Vol. 12:49-56.

Asari, F. F. A. H., Baharuddin, N. S., Jusoh, N., Mohamad, Z., Shamsudin, N., & Jusoff, K. (2011). A vector error correction model (VECM) approach in explaining the relationship between interest rate and inflation towards exchange rate volatility in Malaysia. *World Applied Sciences Journal*, *12*(3), 49-56.

Asiamah, N., Mensah, H. K., & Oteng-Abayie, E. F. (2017). General, target, and accessible population: Demystifying the concepts for effective sampling. *The Qualitative Report*, *22*(6), 1607.

Asif , Razzaq & Aima. (2015). Dynamic Relationship between Income and Consumption: A Time Series Analysis of Spain.

Bayar, A., & Mc Morrow, K. (1999). *Determinants of private consumption* (No. 135). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Bonsu, C.O. & Muzindutsi, P.F., (2017). Macroeconomic Determinants of Household Consumption Expenditure in Ghana: A Multivariate Cointegration Approach. *International Journal of Economics and Financial Issues*, *7*(4), pp.737-745.

Borooah, V. K. & D. R. Sharpe (1986). 'Aggregate Consumption and the Distribution of Income in the United Kingdom: An Econometric Analysis'. *The Economic Journal,* Vol. 382:449-466.

Burda, M. & C. Wyplosz (2009). *Macroeconomics: A European Text.* Fifth Edition. Oxford University Press, United Kingdom.

Campbell, J. & A. Deaton (1989). 'Why is Consumption So Smooth?' *The Review of Economic Studies,* Vol. 56(3):357-373.

Campbell, J. Y. & N. G. Mankiw (1990). 'Permanent Income, Current Income, and Consumption'. *Journal of Business & Economic Statistics,* Vol. 8(3):265-279.

Carrol, C. D. (2000). 'Requiem for the Representative Consumer? Aggregate Implications of Microeconomic Consumption Behaviour'. *The American Economic Review,* Vol. 90(2):110-115.

Da Saliva, F. M., Coronel, D. A. & K. M., Vieira, 2014. Causality and Cointegration Analysis between Macroeconomic Variables and Bovespa. *PLoS One* 9(2): e89765. Doi:10.1371/journal.pone.0089765

da Silva, F. M., Coronel, D. A., & Vieira, K. M. (2014). Causality and cointegration analysis between macroeconomic variables and the Bovespa. *PLoS One*, *9*(2), e89765.

Dagdeviren, H., Balasuriya, J., Luz, S., Malik, A., & Shah, H. (2020). Financialization, welfare retrenchment and subsistence debt in Britain. *New political economy*, *25*(2), 159-173.

Davidson, J., 1997. Structural relations, cointegration and identification: some simple results and their application. *Journal of Econometrics,* Volume 87: 87 – 113.

DiGaetano, R. (2013). Sample frame and related sample design issues for surveys of physicians and physician practices. *Evaluation & the health professions*, *36*(3), 296-329.

Enders, W., (2015). '*Applied Econometric Series.* Fourth Edition. John Wiley & Sons, New Jersey. USA.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276.

Ericsson, N. R., 1991. *Cointegration, Exogeneity, and Policy Analysis: An Overview*. Board of Governors of the Federal Reserve System: International Finance Discussion Papers.

Goldstein, A. (2013). Inequality, Financialization, and the Growth of Household Debt in the US, 1989-2007. *Institute for New Economic Thinking (INET) Grantee Paper*.

Hafer, R. W., & Jansen, D. W. (1991). The demand for money in the United States: evidence from cointegration tests. *Journal of Money, Credit and Banking*, *23*(2), 155-168.Economic and Financial Affairs (DG ECFIN), European Commission.

IDC (2013). South African Economy: An overview of Key trends since 1994

IDC (2019). Economic Overview: Recent developments in the South African Economy, Department of Research and Information

IDC (2020). Economic Overview: Recent developments in the South African Economy, Department of Research and Information

IDC, (2018). *Economic Trends: Key trends in the South African economy*, Department of Research and Information

Kaboub, F. (2008). Positivist paradigm. *Encyclopaedia of Counselling*, *2*(2), 343.

Keele, L., & Boef, S.L. (2004). Not Just for Cointegration: Error Correction Models with Stationary Data.

Khan, H.H.A., Abdullah, H. & Samsudin, S., (2016). The Linkages between Household Consumption and Household Debt Composition in Malaysia. *International Journal of Economics and Financial Issues*, *6*(4), pp.1354-1359.

Kivunja, C., & Kuyini, A. B. (2017). Understanding and Applying Research Paradigms in Educational Contexts. *International Journal of higher education*, *6*(5), 26-41.

Landsem, J. (2016). '*An investigation of the Norwegian consumption function: Income distribution and wealth effects*. Statistics Norway, 12 September 2016

Mankiw, N.G., (1997). *Macroeconomics*. Third Edition. Worth Publishers, Inc., New York, USA.

Masih, A. M., & Masih, R. (1998). A multivariate cointegrated modelling approach in testing temporal causality between energy consumption, real income and prices with an application to two Asian LDCs. *Applied Economics*, *30*(10), 1287-1298.

Masih, A.M. M &R. Masih (1997). 'On the Temporal Causal Relationship between Energy Consumption, Real Income, and Prices: Some New Evidence from Asian-Energy Dependent NICs Based on a Multivariate Cointegration/Vector Error-Correction Approach'. *Journal of Policy Modelling*, Vol. 19(4):417-440

Mboweni.(2019).Medium Term Budget Policy Statement. http://www.treasury.gov.za/documents/mtbps/2019/mtbps/Chapter%202.pdf (accessed on 23 January 2021)

Meniago, C., Mukuddem-Petersen, J., Petersen, M.A. & Mongale, I.P., (2013). What causes household debt to increase in South Africa? *Economic Modelling*, *33*, pp.482-492.

Mourad, M. (2014). *Macrodynamics of Household Debt Accumulation and Consumption.* The University of New South Wales School of Economics, Honours Thesis, 85.

Muellbauer, J., & Lattimore, R. (2011). The Consumption Function: A Theoretical and Empirical Overview. (M. Pesaran, Ed.). azzaq,

National Treasury (2019). Economic Outlook, National Treasury of the Republic of South Africa, Pretoria, http://www.treasury.gov.za.

Nicklaus, C., (2015). *The effect of household income on household consumption in China.* Master programme in International Economics

Pehkonen, J. (1994). 'Testing Weak Exogeneity by Multivariate Cointegration Techniques: The Demand for Labour in Finish Manufacturing'. *Finish Economic Papers,* Vol.7 (2):108-119.

Radebe, D. L. T. (2019). *The use of traditional folk media to convey diabetes messages at public health care services* (Doctoral dissertation, University of the Free State).

SARB (2020). Full Quartely Bulletin – No 298. https://www.resbank.co.za/en/home/publications/publication-detail-pages/quarterly-bulletins/quarterly-bulletin-publications/2020

Singh, B. (2004). *Modelling real private consumption expenditure: an empirical study on Fiji*. Economics Department, Reserve Bank of Fiji.

South African Reserve Bank, Quarterly Bulletin March 2018 No. 287

Turner, P. (1993). *Modern Macroeconomic Analysis*. McGraw-Hill, New York, USA

Usman, M., Fatin, D. F., Barusman, M. Y. S., & Elfaki, F. A. (2017). Application of Vector Error Correction Model (VECM) and Impulse Response Function for Analysis Data Index of Farmers' Terms of Trade. *Indian Journal of Science and Technology*, *10*(19).

Welman, C. Kruger, F. & Mitchell, B. (2005). *Research Methodology.* 3rd ed. Cape Town: Oxford University Press

Wong Wei Xuan, R. (2016). An Analysis of Household Debt on Consumption : in the Swedish Economy (Dissertation).Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:umu:diva-135681

APPENDICES

APPENDIX 1: UNIT ROOT TEST ADF

Null Hypothesis: LPCE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.783983	1.0000
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LPCE)
Method: Least Squares
Date: 04/27/21 Time: 13:29
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPCE(-1)	0.010877	0.003907	2.783983	0.0059
C	-0.054899	0.035237	-1.557962	0.1208
@TREND("1969M01")	-0.000474	0.000127	-3.744604	0.0002

R-squared	0.247398	Mean dependent var	0.030339
Adjusted R-squared	0.239872	S.D. dependent var	0.015677
S.E. of regression	0.013668	Akaike info criterion	-5.732849
Sum squared resid	0.037363	Schwarz criterion	-5.683886
Log likelihood	584.8842	Hannan-Quinn criter.	-5.713041
F-statistic	32.87232	Durbin-Watson stat	1.763985
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LPCE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.613960	0.0000
Test critical values:	1% level	-4.004599	
	5% level	-3.432452	
	10% level	-3.139991	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LPCE,2)
Method: Least Squares
Date: 04/27/21 Time: 13:32
Sample (adjusted): 1970M01 2019M04
Included observations: 200 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LPCE(-1))	-0.573264	0.102114	-5.613960	0.0000
D(LPCE(-1),2)	-0.339134	0.091318	-3.713757	0.0003
D(LPCE(-2),2)	-0.209898	0.069479	-3.021038	0.0029
C	0.025499	0.004844	5.264218	0.0000
@TREND("1969M01")	-7.87E-05	2.07E-05	-3.795890	0.0002

R-squared	0.467936	Mean dependent var	-7.86E-05
Adjusted R-squared	0.457022	S.D. dependent var	0.018086
S.E. of regression	0.013327	Akaike info criterion	-5.773398
Sum squared resid	0.034633	Schwarz criterion	-5.690940
Log likelihood	582.3398	Hannan-Quinn criter.	-5.740029
F-statistic	42.87433	Durbin-Watson stat	2.054056
Prob(F-statistic)	0.000000		

Null Hypothesis: LPCE has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		1.663917	1.0000
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000184
HAC corrected variance (Bartlett kernel)	0.000375

Phillips-Perron Test Equation
Dependent Variable: D(LPCE)
Method: Least Squares
Date: 04/27/21 Time: 13:38
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPCE(-1)	0.010877	0.003907	2.783983	0.0059
C	-0.054899	0.035237	-1.557962	0.1208
@TREND("1969M01")	-0.000474	0.000127	-3.744604	0.0002

R-squared	0.247398	Mean dependent var	0.030339
Adjusted R-squared	0.239872	S.D. dependent var	0.015677
S.E. of regression	0.013668	Akaike info criterion	-5.732849
Sum squared resid	0.037363	Schwarz criterion	-5.683886
Log likelihood	584.8842	Hannan-Quinn criter.	-5.713041
F-statistic	32.87232	Durbin-Watson stat	1.763985
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LPCE) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-13.00134	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000187
HAC corrected variance (Bartlett kernel)	0.000318

Phillips-Perron Test Equation
Dependent Variable: D(LPCE,2)
Method: Least Squares
Date: 04/27/21 Time: 13:41
Sample (adjusted): 1969M03 2019M04
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LPCE(-1))	-0.841890	0.069907	-12.04302	0.0000
C	0.036467	0.003595	10.14429	0.0000
@TREND("1969M01")	-0.000107	1.87E-05	-5.701396	0.0000

R-squared	0.421609	Mean dependent var	-9.76E-05
Adjusted R-squared	0.415796	S.D. dependent var	0.018010
S.E. of regression	0.013766	Akaike info criterion	-5.718552
Sum squared resid	0.037709	Schwarz criterion	-5.669419
Log likelihood	580.5737	Hannan-Quinn criter.	-5.698672
F-statistic	72.52904	Durbin-Watson stat	2.051949
Prob(F-statistic)	0.000000		

Null Hypothesis: LHDI has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.372983	0.0000
Test critical values:	1% level	-3.463067	
	5% level	-2.875825	
	10% level	-2.574462	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LHDI)
Method: Least Squares
Date: 04/27/21 Time: 13:46
Sample (adjusted): 1970M01 2019M04
Included observations: 200 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LHDI(-1)	-0.008463	0.001575	-5.372983	0.0000
D(LHDI(-1))	-0.504626	0.068490	-7.367888	0.0000
D(LHDI(-2))	-0.455343	0.069768	-6.526519	0.0000
D(LHDI(-3))	-0.208425	0.068271	-3.052923	0.0026
C	0.169896	0.021777	7.801646	0.0000

R-squared	0.287954	Mean dependent var	0.030172
Adjusted R-squared	0.273348	S.D. dependent var	0.044793
S.E. of regression	0.038184	Akaike info criterion	-3.668144
Sum squared resid	0.284306	Schwarz criterion	-3.585686
Log likelihood	371.8144	Hannan-Quinn criter.	-3.634775
F-statistic	19.71467	Durbin-Watson stat	1.984578
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LHDI,2)
Method: Least Squares
Date: 04/27/21 Time: 13:47
Sample (adjusted): 1971M02 2019M04
Included observations: 195 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHDI(-1))	-0.886092	0.275742	-3.213485	0.0015
D(LHDI(-1),2)	-0.517707	0.262071	-1.975449	0.0497
D(LHDI(-2),2)	-0.804139	0.249377	-3.224591	0.0015
D(LHDI(-3),2)	-0.818227	0.236079	-3.465894	0.0007
D(LHDI(-4),2)	-0.638076	0.213562	-2.987777	0.0032
D(LHDI(-5),2)	-0.404963	0.174832	-2.316305	0.0216
D(LHDI(-6),2)	-0.264996	0.123484	-2.145996	0.0332
D(LHDI(-7),2)	-0.230398	0.070394	-3.272969	0.0013

C	0.026145	0.008808	2.968183	0.0034

R-squared	0.718412	Mean dependent var	-0.000568
Adjusted R-squared	0.706301	S.D. dependent var	0.071318
S.E. of regression	0.038650	Akaike info criterion	-3.623474
Sum squared resid	0.277854	Schwarz criterion	-3.472412
Log likelihood	362.2887	Hannan-Quinn criter.	-3.562311
F-statistic	59.31751	Durbin-Watson stat	2.034387
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LHDI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.85911	0.0000
Test critical values:	1% level	-4.004599	
	5% level	-3.432452	
	10% level	-3.139991	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LHDI,2)
Method: Least Squares
Date: 04/27/21 Time: 16:09
Sample (adjusted): 1970M01 2019M04
Included observations: 200 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHDI(-1))	-2.220211	0.160199	-13.85911	0.0000
D(LHDI(-1),2)	0.696615	0.116135	5.998330	0.0000
D(LHDI(-2),2)	0.223542	0.068253	3.275227	0.0012
C	0.096269	0.008734	11.02237	0.0000
@TREND("1969M01")	-0.000285	5.02E-05	-5.683505	0.0000

R-squared	0.727847	Mean dependent var	0.000151
Adjusted R-squared	0.722264	S.D. dependent var	0.071904
S.E. of regression	0.037894	Akaike info criterion	-3.683364
Sum squared resid	0.280012	Schwarz criterion	-3.600906
Log likelihood	373.3364	Hannan-Quinn criter.	-3.649994
F-statistic	130.3771	Durbin-Watson stat	1.993298
Prob(F-statistic)	0.000000		

Null Hypothesis: LHDI has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.197938	0.0215
Test critical values:	1% level	-3.462574	
	5% level	-2.875608	

	10% level	-2.574346

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001940
HAC corrected variance (Bartlett kernel)	0.000855

Phillips-Perron Test Equation
Dependent Variable: D(LHDI)
Method: Least Squares
Date: 04/27/21 Time: 16:11
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LHDI(-1)	-0.003703	0.001670	-2.217676	0.0277
C	0.075280	0.020810	3.617536	0.0004

R-squared	0.023884	Mean dependent var	0.029648
Adjusted R-squared	0.019027	S.D. dependent var	0.044696
S.E. of regression	0.044269	Akaike info criterion	-3.387277
Sum squared resid	0.393902	Schwarz criterion	-3.354634
Log likelihood	345.8086	Hannan-Quinn criter.	-3.374071
F-statistic	4.918089	Durbin-Watson stat	2.603888
Prob(F-statistic)	0.027697		

Null Hypothesis: D(LHDI) has a unit root
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-19.83166	0.0000
Test critical values:	1% level	-3.462737	
	5% level	-2.875680	
	10% level	-2.574385	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001844
HAC corrected variance (Bartlett kernel)	0.001345

Phillips-Perron Test Equation
Dependent Variable: D(LHDI,2)
Method: Least Squares
Date: 04/27/21 Time: 16:12
Sample (adjusted): 1969M03 2019M04
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHDI(-1))	-1.276595	0.067959	-18.78470	0.0000
C	0.037957	0.003647	10.40653	0.0000

R-squared	0.638248	Mean dependent var	-1.11E-05
Adjusted R-squared	0.636439	S.D. dependent var	0.071567
S.E. of regression	0.043152	Akaike info criterion	-3.438329
Sum squared resid	0.372417	Schwarz criterion	-3.405574
Log likelihood	349.2713	Hannan-Quinn criter.	-3.425077
F-statistic	352.8650	Durbin-Watson stat	2.166693
Prob(F-statistic)	0.000000		

Null Hypothesis: LHDI has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.566435	0.9994
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001940
HAC corrected variance (Bartlett kernel)	0.000859

Phillips-Perron Test Equation
Dependent Variable: D(LHDI)
Method: Least Squares
Date: 04/27/21 Time: 16:15
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LHDI(-1)	-0.004471	0.012891	-0.346857	0.7291
C	0.082240	0.117629	0.699153	0.4853
@TREND("1969M01")	2.46E-05	0.000409	0.060123	0.9521

R-squared	0.023901	Mean dependent var	0.029648
Adjusted R-squared	0.014140	S.D. dependent var	0.044696
S.E. of regression	0.044379	Akaike info criterion	-3.377443
Sum squared resid	0.393895	Schwarz criterion	-3.328479
Log likelihood	345.8104	Hannan-Quinn criter.	-3.357634
F-statistic	2.448662	Durbin-Watson stat	2.601933
Prob(F-statistic)	0.088996		

Null Hypothesis: LHDI has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*

Phillips-Perron test statistic		0.566435	0.9994
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001940
HAC corrected variance (Bartlett kernel)	0.000859

Phillips-Perron Test Equation
Dependent Variable: D(LHDI)
Method: Least Squares
Date: 04/27/21 Time: 16:16
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LHDI(-1)	-0.004471	0.012891	-0.346857	0.7291
C	0.082240	0.117629	0.699153	0.4853
@TREND("1969M01")	2.46E-05	0.000409	0.060123	0.9521

R-squared	0.023901	Mean dependent var	0.029648
Adjusted R-squared	0.014140	S.D. dependent var	0.044696
S.E. of regression	0.044379	Akaike info criterion	-3.377443
Sum squared resid	0.393895	Schwarz criterion	-3.328479
Log likelihood	345.8104	Hannan-Quinn criter.	-3.357634
F-statistic	2.448662	Durbin-Watson stat	2.601933
Prob(F-statistic)	0.088996		

Null Hypothesis: D(LHDI) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-23.03983	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001763
HAC corrected variance (Bartlett kernel)	0.000832

Phillips-Perron Test Equation
Dependent Variable: D(LHDI,2)
Method: Least Squares
Date: 04/27/21 Time: 16:18
Sample (adjusted): 1969M03 2019M04

Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHDI(-1))	-1.307134	0.067389	-19.39680	0.0000
C	0.054827	0.006639	8.258731	0.0000
@TREND("1969M01")	-0.000156	5.16E-05	-3.016046	0.0029

R-squared	0.654061	Mean dependent var	-1.11E-05
Adjusted R-squared	0.650585	S.D. dependent var	0.071567
S.E. of regression	0.042304	Akaike info criterion	-3.473126
Sum squared resid	0.356138	Schwarz criterion	-3.423993
Log likelihood	353.7857	Hannan-Quinn criter.	-3.453246
F-statistic	188.1232	Durbin-Watson stat	2.224033
Prob(F-statistic)	0.000000		

Null Hypothesis: LDSR has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.135348	0.0256
Test critical values:	1% level	-3.463235	
	5% level	-2.875898	
	10% level	-2.574501	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LDSR)
Method: Least Squares
Date: 04/27/21 Time: 16:23
Sample (adjusted): 1970M02 2019M04
Included observations: 199 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDSR(-1)	-0.095633	0.030501	-3.135348	0.0020
D(LDSR(-1))	-0.337262	0.068481	-4.924889	0.0000
D(LDSR(-2))	-0.408363	0.069996	-5.834102	0.0000
D(LDSR(-3))	-0.245584	0.068819	-3.568559	0.0005
D(LDSR(-4))	-0.319214	0.065932	-4.841522	0.0000
C	0.348086	0.102745	3.387848	0.0009

R-squared	0.277394	Mean dependent var	0.015417
Adjusted R-squared	0.258674	S.D. dependent var	0.431350
S.E. of regression	0.371394	Akaike info criterion	0.886580
Sum squared resid	26.62114	Schwarz criterion	0.985875
Log likelihood	-82.21466	Hannan-Quinn criter.	0.926767
F-statistic	14.81779	Durbin-Watson stat	2.041686
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LDSR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=14)

	t-Statistic	Prob.*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.81668	0.0000
Test critical values:	1% level	-4.004836	
	5% level	-3.432566	
	10% level	-3.140059	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LDSR,2)
Method: Least Squares
Date: 04/27/21 Time: 16:27
Sample (adjusted): 1970M02 2019M04
Included observations: 199 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDSR(-1))	-2.461212	0.192032	-12.81668	0.0000
D(LDSR(-1),2)	1.061125	0.156377	6.785700	0.0000
D(LDSR(-2),2)	0.606071	0.112267	5.398486	0.0000
D(LDSR(-3),2)	0.333910	0.067395	4.954532	0.0000
C	0.126455	0.056366	2.243469	0.0260
@TREND("1969M01")	-0.000854	0.000472	-1.809887	0.0719

R-squared	0.696971	Mean dependent var	0.002038
Adjusted R-squared	0.689121	S.D. dependent var	0.677130
S.E. of regression	0.377544	Akaike info criterion	0.919429
Sum squared resid	27.51017	Schwarz criterion	1.018725
Log likelihood	-85.48323	Hannan-Quinn criter.	0.959617
F-statistic	88.78076	Durbin-Watson stat	2.042084
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LDSR) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.61569	0.0000
Test critical values:	1% level	-3.463235	
	5% level	-2.875898	
	10% level	-2.574501	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LDSR,2)
Method: Least Squares
Date: 04/27/21 Time: 16:25
Sample (adjusted): 1970M02 2019M04
Included observations: 199 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDSR(-1))	-2.407407	0.190826	-12.61569	0.0000
D(LDSR(-1),2)	1.018084	0.155462	6.548778	0.0000
D(LDSR(-2),2)	0.577605	0.111810	5.165964	0.0000
D(LDSR(-3),2)	0.321090	0.067414	4.762992	0.0000
C	0.036832	0.027084	1.359936	0.1754

R-squared	0.691828	Mean dependent var	0.002038
Adjusted R-squared	0.685474	S.D. dependent var	0.677130
S.E. of regression	0.379752	Akaike info criterion	0.926209
Sum squared resid	27.97708	Schwarz criterion	1.008956
Log likelihood	-87.15782	Hannan-Quinn criter.	0.959699
F-statistic	108.8798	Durbin-Watson stat	2.027927
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LDSR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.81668	0.0000
Test critical values:	1% level	-4.004836	
	5% level	-3.432566	
	10% level	-3.140059	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LDSR,2)
Method: Least Squares
Date: 04/27/21 Time: 16:27
Sample (adjusted): 1970M02 2019M04
Included observations: 199 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDSR(-1))	-2.461212	0.192032	-12.81668	0.0000
D(LDSR(-1),2)	1.061125	0.156377	6.785700	0.0000
D(LDSR(-2),2)	0.606071	0.112267	5.398486	0.0000
D(LDSR(-3),2)	0.333910	0.067395	4.954532	0.0000
C	0.126455	0.056366	2.243469	0.0260
@TREND("1969M01")	-0.000854	0.000472	-1.809887	0.0719

R-squared	0.696971	Mean dependent var	0.002038
Adjusted R-squared	0.689121	S.D. dependent var	0.677130
S.E. of regression	0.377544	Akaike info criterion	0.919429
Sum squared resid	27.51017	Schwarz criterion	1.018725
Log likelihood	-85.48323	Hannan-Quinn criter.	0.959617
F-statistic	88.78076	Durbin-Watson stat	2.042084
Prob(F-statistic)	0.000000		

Null Hypothesis: LDSR has a unit root
Exogenous: Constant
Bandwidth: 35 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.475303	0.0003
Test critical values:	1% level	-3.462574	
	5% level	-2.875608	
	10% level	-2.574346	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.170673
HAC corrected variance (Bartlett kernel)	0.227237

Phillips-Perron Test Equation
Dependent Variable: D(LDSR)
Method: Least Squares
Date: 04/27/21 Time: 16:31
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDSR(-1)	-0.124921	0.030041	-4.158374	0.0000
C	0.419914	0.100827	4.164686	0.0000

R-squared	0.079215	Mean dependent var	0.018528
Adjusted R-squared	0.074634	S.D. dependent var	0.431595
S.E. of regression	0.415177	Akaike info criterion	1.089578
Sum squared resid	34.64669	Schwarz criterion	1.122220
Log likelihood	-108.5921	Hannan-Quinn criter.	1.102784
F-statistic	17.29207	Durbin-Watson stat	2.340789
Prob(F-statistic)	0.000047		

Null Hypothesis: D(LDSR) has a unit root
Exogenous: Constant
Bandwidth: 41 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-26.43905	0.0000
Test critical values:	1% level	-3.462737	
	5% level	-2.875680	
	10% level	-2.574385	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.177042
HAC corrected variance (Bartlett kernel)	0.038372

Phillips-Perron Test Equation
Dependent Variable: D(LDSR,2)
Method: Least Squares
Date: 04/27/21 Time: 16:32
Sample (adjusted): 1969M03 2019M04
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDSR(-1))	-1.222602	0.068936	-17.73520	0.0000
C	0.022765	0.029780	0.764422	0.4455

R-squared	0.611301	Mean dependent var	6.60E-18
Adjusted R-squared	0.609358	S.D. dependent var	0.676565
S.E. of regression	0.422862	Akaike info criterion	1.126312

Sum squared resid	35.76252	Schwarz criterion	1.159067
Log likelihood	-111.7575	Hannan-Quinn criter.	1.139565
F-statistic	314.5373	Durbin-Watson stat	2.114815
Prob(F-statistic)	0.000000		

Null Hypothesis: LDSR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.501823	0.0000
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.160973
HAC corrected variance (Bartlett kernel)	0.166596

Phillips-Perron Test Equation
Dependent Variable: D(LDSR)
Method: Least Squares
Date: 04/27/21 Time: 16:34
Sample (adjusted): 1969M02 2019M04
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDSR(-1)	-0.235871	0.043322	-5.444625	0.0000
C	0.522480	0.102514	5.096668	0.0000
@TREND("1969M01")	0.002490	0.000717	3.471660	0.0006

R-squared	0.131550	Mean dependent var	0.018528
Adjusted R-squared	0.122865	S.D. dependent var	0.431595
S.E. of regression	0.404212	Akaike info criterion	1.040914
Sum squared resid	32.67748	Schwarz criterion	1.089877
Log likelihood	-102.6527	Hannan-Quinn criter.	1.060723
F-statistic	15.14767	Durbin-Watson stat	2.215543
Prob(F-statistic)	0.000001		

Null Hypothesis: D(LDSR) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 38 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-34.92519	0.0001
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.176234
HAC corrected variance (Bartlett kernel)	0.019436

Phillips-Perron Test Equation
Dependent Variable: D(LDSR,2)
Method: Least Squares
Date: 04/27/21 Time: 16:35
Sample (adjusted): 1969M03 2019M04
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDSR(-1))	-1.226113	0.069049	-17.75707	0.0000
C	0.072887	0.060320	1.208326	0.2284
@TREND("1969M01")	-0.000488	0.000511	-0.955563	0.3405

R-squared	0.613077	Mean dependent var	6.60E-18
Adjusted R-squared	0.609188	S.D. dependent var	0.676565
S.E. of regression	0.422954	Akaike info criterion	1.131635
Sum squared resid	35.59917	Schwarz criterion	1.180767
Log likelihood	-111.2951	Hannan-Quinn criter.	1.151514
F-statistic	157.6569	Durbin-Watson stat	2.119510
Prob(F-statistic)	0.000000		

APPENDIX 2: LAG ORDER SELECTION

VAR Lag Order Selection Criteria
Endogenous variables: LPCE LHDI LDSR
Exogenous variables: C
Date: 04/27/21 Time: 16:50
Sample: 1969M01 2019M04
Included observations: 196

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-163.2124	NA	0.001094	1.696045	1.746220	1.716359
1	859.9972	2004.656	3.50e-08	-8.653033	-8.452332*	-8.571779*
2	866.0143	11.60433	3.61e-08	-8.622594	-8.271368	-8.480401
3	878.6993	24.07561	3.48e-08	-8.660196	-8.158444	-8.457063
4	889.5098	20.18700	3.42e-08	-8.678671	-8.026393	-8.414598
5	907.0588	32.23283	3.13e-08	-8.765906	-7.963102	-8.440892
6	920.0083	23.38854*	3.01e-08*	-8.806208*	-7.852878	-8.420254
7	927.8069	13.84647	3.05e-08	-8.793948	-7.690093	-8.347055
8	933.7777	10.41832	3.15e-08	-8.763037	-7.508657	-8.255204

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

APPENDIX 3: COINTEGRATION TESTS

Date: 04/27/21 Time: 16:54
Sample (adjusted): 1969M04 2019M04
Included observations: 201 after adjustments
Trend assumption: Linear deterministic trend
Series: LPCE LHDI LDSR
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.205963	89.04345	29.79707	0.0000
At most 1 *	0.123863	42.68770	15.49471	0.0000
At most 2 *	0.077016	16.10892	3.841465	0.0001

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.205963	46.35574	21.13162	0.0000
At most 1 *	0.123863	26.57878	14.26460	0.0004
At most 2 *	0.077016	16.10892	3.841465	0.0001

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LPCE	LHDI	LDSR
45.29542	-46.18208	-0.306161
-1.852102	0.768674	1.743502
5.161885	-5.214469	1.074191

Unrestricted Adjustment Coefficients (alpha):

D(LPCE)	-0.000442	0.003189	-0.002978
D(LHDI)	0.015190	0.006639	-0.001275
D(LDSR)	0.041754	-0.099606	-0.072741

1 Cointegrating Equation(s): Log likelihood 877.4961

Normalized cointegrating coefficients (standard error in parentheses)

LPCE	LHDI	LDSR
1.000000	-1.019575	-0.006759
	(0.00349)	(0.00641)

Adjustment coefficients (standard error in parentheses)

D(LPCE)	-0.020009	
	(0.04588)	
D(LHDI)	0.688024	
	(0.11603)	
D(LDSR)	1.891261	
	(1.28580)	

2 Cointegrating Equation(s): Log likelihood 890.7854

Normalized cointegrating coefficients (standard error in parentheses)

LPCE	LHDI	LDSR
1.000000	0.000000	-1.582980
		(0.20494)
0.000000	1.000000	-1.545959
		(0.20108)

Adjustment coefficients (standard error in parentheses)

D(LPCE)	-0.025916	0.022853
	(0.04472)	(0.04557)
D(LHDI)	0.675728	-0.696389
	(0.11409)	(0.11624)
D(LDSR)	2.075741	-2.004847
	(1.24515)	(1.26864)

Vector Error Correction Estimates
Date: 04/27/21 Time: 17:09
Sample (adjusted): 1969M04 2019M04
Included observations: 201 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
LPCE(-1)	1.000000		
LHDI(-1)	-0.851994		
	(0.03199)		
	[-26.6347]		
LDSR(-1)	-0.084081		
	(0.01286)		
	[-6.53575]		
@TREND(69M01)	-0.004482		
	(0.00090)		
	[-4.97719]		
C	-1.057586		
Error Correction:	**D(LPCE)**	**D(LHDI)**	**D(LDSR)**
CointEq1	0.039303	0.266943	5.385150
	(0.03276)	(0.08831)	(0.84123)
	[1.19970]	[3.02286]	[6.40152]
D(LPCE(-1))	0.184073	0.316710	-4.046702
	(0.07715)	(0.20797)	(1.98110)
	[2.38586]	[1.52290]	[-2.04266]
D(LPCE(-2))	0.231669	0.395522	-2.352396
	(0.07432)	(0.20034)	(1.90843)

	[3.11711]	[1.97428]	[-1.23263]
D(LHDI(-1))	0.055239	-0.316640	3.670955
	(0.03074)	(0.08286)	(0.78930)
	[1.79707]	[-3.82152]	[4.65088]
D(LHDI(-2))	0.047795	-0.320211	2.856873
	(0.02753)	(0.07422)	(0.70700)
	[1.73588]	[-4.31450]	[4.04082]
D(LDSR(-1))	0.001229	0.007898	-0.048376
	(0.00283)	(0.00763)	(0.07268)
	[0.43408]	[1.03527]	[-0.66564]
D(LDSR(-2))	0.000738	0.006967	-0.130009
	(0.00260)	(0.00701)	(0.06683)
	[0.28365]	[0.99317]	[-1.94552]
C	0.014591	0.026945	0.018571
	(0.00269)	(0.00725)	(0.06910)
	[5.42223]	[3.71463]	[0.26875]
R-squared	0.202439	0.284763	0.298506
Adj. R-squared	0.173512	0.258822	0.273063
Sum sq. resids	0.039545	0.287332	26.07438
S.E. equation	0.014314	0.038585	0.367560
F-statistic	6.998253	10.97724	11.73242
Log likelihood	572.4221	373.1107	-79.95029
Akaike AIC	-5.616141	-3.632943	0.875127
Schwarz SC	-5.484666	-3.501468	1.006602
Mean dependent	0.030372	0.029925	0.015264
S.D. dependent	0.015745	0.044818	0.431102

Determinant resid covariance (dof adj.)	3.53E-08
Determinant resid covariance	3.13E-08
Log likelihood	881.0837
Akaike information criterion	-8.488395
Schwarz criterion	-8.028233
Number of coefficients	28

APPENDIX 4: ERROR CORRECTION MODEL

Vector Error Correction Estimates
Date: 04/27/21 Time: 17:20
Sample (adjusted): 1969M04 2019M04
Included observations: 201 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2
LPCE(-1)	1.000000	0.000000
LHDI(-1)	0.000000	1.000000
LDSR(-1)	-1.582980	-1.545959
	(0.20547)	(0.20161)
	[-7.70406]	[-7.66825]
C	-7.183203	-7.340146

Error Correction:	D(LPCE)	D(LHDI)	D(LDSR)
CointEq1	-0.025916	0.675728	2.075741
	(0.04484)	(0.11439)	(1.24839)
	[-0.57797]	[5.90746]	[1.66273]
CointEq2	0.022853	-0.696389	-2.004847
	(0.04569)	(0.11654)	(1.27194)
	[0.50021]	[-5.97536]	[-1.57621]
D(LPCE(-1))	0.167324	0.030857	1.363571
	(0.07721)	(0.19697)	(2.14969)
	[2.16706]	[0.15666]	[0.63431]
D(LPCE(-2))	0.198335	0.157722	2.494353
	(0.07489)	(0.19105)	(2.08514)
	[2.64821]	[0.82554]	[1.19625]
D(LHDI(-1))	0.014366	-0.038434	2.170567
	(0.03767)	(0.09611)	(1.04889)
	[0.38133]	[-0.39991]	[2.06940]
D(LHDI(-2))	0.021366	-0.161991	1.898772
	(0.02997)	(0.07645)	(0.83436)
	[0.71293]	[-2.11893]	[2.27572]
D(LDSR(-1))	-0.003675	-0.009571	-0.187424
	(0.00257)	(0.00655)	(0.07152)
	[-1.43057]	[-1.46044]	[-2.62043]
D(LDSR(-2))	-0.002591	-0.005673	-0.212406
	(0.00248)	(0.00634)	(0.06918)
	[-1.04287]	[-0.89495]	[-3.07050]
C	0.018273	0.030422	-0.216709
	(0.00291)	(0.00742)	(0.08094)
	[6.28520]	[4.10199]	[-2.67737]
R-squared	0.238514	0.388395	0.212637
Adj. R-squared	0.206785	0.362912	0.179830
Sum sq. resids	0.037756	0.245700	29.26610
S.E. equation	0.014023	0.035773	0.390420
F-statistic	7.517325	15.24103	6.481479
Log likelihood	577.0739	388.8417	-91.55572
Akaike AIC	-5.652477	-3.779520	1.000554
Schwarz SC	-5.504568	-3.631611	1.148464
Mean dependent	0.030372	0.029925	0.015264
S.D. dependent	0.015745	0.044818	0.431102

Determinant resid covariance (dof adj.)	3.26E-08
Determinant resid covariance	2.84E-08
Log likelihood	890.7854
Akaike information criterion	-8.535179
Schwarz criterion	-7.992845
Number of coefficients	33

APPENDIX 5: DIAGNOSTIC TESTS

VEC Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: No residual autocorrelations up to lag h

Date: 04/27/21 Time: 17:22
Sample: 1969M01 2019M04
Included observations: 201

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	2.022081	---	2.032192	---	---
2	7.658046	---	7.724799	---	---
3	19.54160	0.0763	19.78841	0.0712	12
4	43.09137	0.0031	43.81634	0.0025	21
5	54.34714	0.0042	55.35925	0.0032	30
6	70.81942	0.0014	72.33837	0.0009	39

*Test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution
after adjustment for VEC estimation (Bruggemann, et al. 2005)

VEC Residual Serial Correlation LM Tests
Date: 04/27/21 Time: 17:25
Sample: 1969M01 2019M04
Included observations: 201

Null hypothes is: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	26.83911	9	0.0015	3.047652	(9, 455.3)	0.0015
2	43.36486	9	0.0000	5.014841	(9, 455.3)	0.0000
3	20.32640	9	0.0160	2.291652	(9, 455.3)	0.0160
4	26.00754	9	0.0020	2.950524	(9, 455.3)	0.0020
5	11.49461	9	0.2433	1.283447	(9, 455.3)	0.2433
6	17.33043	9	0.0438	1.947465	(9, 455.3)	0.0438

Null hypothes is: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	26.83911	9	0.0015	3.047652	(9, 455.3)	0.0015
2	57.57193	18	0.0000	3.327897	(18, 520.9)	0.0000
3	73.65404	27	0.0000	2.854640	(27, 529.3)	0.0000
4	90.94416	36	0.0000	2.663831	(36, 526.6)	0.0000
5	95.85117	45	0.0000	2.237523	(45, 520.7)	0.0000
6	110.3615	54	0.0000	2.158532	(54, 513.3)	0.0000

*Edgeworth expansion corrected likelihood ratio statistic.

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal

Date: 04/27/21 Time: 17:25
Sample: 1969M01 2019M04
Included observations: 201

Component	Skewness	Chi-sq	df	Prob.*
1	-0.605647	12.28810	1	0.0005
2	0.498872	8.337250	1	0.0039
3	-0.213439	1.526128	1	0.2167
Joint		22.15147	3	0.0001

Component	Kurtosis	Chi-sq	df	Prob.
1	6.232226	87.49600	1	0.0000
2	9.155216	317.3010	1	0.0000
3	4.113997	10.39328	1	0.0013
Joint		415.1902	3	0.0000

Component	Jarque-Bera	df	Prob.
1	99.78409	2	0.0000
2	325.6382	2	0.0000
3	11.91941	2	0.0026
Joint	437.3417	6	0.0000

*Approximate p-values do not account for coefficient estimation

VEC Residual Heteroskedasticity Tests (Levels and Squares)
Date: 04/27/21 Time: 17:26
Sample: 1969M01 2019M04
Included observations: 201

Joint test:

Chi-sq	df	Prob.
175.8303	96	0.0000

Individual components:

Dependent	R-squared	F(16,184)	Prob.	Chi-sq(16)	Prob.
res1*res1	0.064368	0.791158	0.6944	12.93798	0.6773
res2*res2	0.178816	2.504165	0.0017	35.94197	0.0029
res3*res3	0.219574	3.235539	0.0001	44.13434	0.0002
res2*res1	0.128247	1.691816	0.0513	25.77772	0.0572
res3*res1	0.159665	2.185013	0.0070	32.09260	0.0097
res3*res2	0.125962	1.657322	0.0584	25.31835	0.0644

VEC Residual Heteroskedasticity Tests (Includes Cross Terms)
Date: 04/27/21 Time: 17:27
Sample: 1969M01 2019M04
Included observations: 201

Joint test:

Chi-sq	df	Prob.
508.5716	264	0.0000

Individual components:

Dependent	R-squared	F(44,156)	Prob.	Chi-sq(44)	Prob.
res1*res1	0.163529	0.693131	0.9216	32.86928	0.8910
res2*res2	0.603170	5.388993	0.0000	121.2372	0.0000
res3*res3	0.463725	3.065803	0.0000	93.20866	0.0000
res2*res1	0.451717	2.921017	0.0000	90.79517	0.0000
res3*res1	0.399480	2.358518	0.0001	80.29544	0.0007
res3*res2	0.468483	3.124985	0.0000	94.16501	0.0000

Impulse

Response of LPCE:	:		
Period	LPCE	LHDI	LDSR
1	0.014023	0.000000	0.000000
2	0.016562	0.001147	0.000780
3	0.020110	0.001778	0.001758
4	0.021485	0.001195	0.003620
5	0.022918	0.000944	0.005362
6	0.024057	0.000698	0.006986
7	0.025101	0.000166	0.008520
8	0.026057	-0.000364	0.009994
9	0.026976	-0.000820	0.011371
10	0.027840	-0.001286	0.012644
Response of LHDI:			
Period	LPCE	LHDI	LDSR
1	0.012929	0.033355	0.000000
2	0.013239	0.008968	-0.001021
3	0.015344	-0.001051	0.001145
4	0.018814	0.005108	0.004520
5	0.020948	0.003833	0.005023
6	0.022253	0.000524	0.005971
7	0.023606	0.000323	0.007998
8	0.024845	0.000294	0.009445
9	0.025863	-0.000520	0.010556
10	0.026767	-0.001155	0.011854
Response of LDSR:			
Period	LPCE	LHDI	LDSR
1	0.036921	-0.046600	0.385866

2	0.073490	-0.023650	0.241603
3	0.116590	-0.017278	0.144147
4	0.106318	-0.078656	0.173575
5	0.108398	-0.066477	0.171266
6	0.112158	-0.041922	0.149096
7	0.107434	-0.051460	0.138047
8	0.101944	-0.053654	0.133080
9	0.098412	-0.045054	0.126181
10	0.094236	-0.042224	0.118155

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: LPCE LHDI LDSR

APPENDIX 6: VARIANCE DECOMPOSITION

Variance Decomposition of LPCE: Period	S.E.	LPCE	LHDI	LDSR
1	0.014023	100.0000	0.000000	0.000000
2	0.021746	99.59311	0.278344	0.128542
3	0.029725	99.07437	0.506936	0.418699
4	0.036874	98.32989	0.434479	1.235626
5	0.043756	97.26550	0.355102	2.379394
6	0.050424	96.00230	0.286574	3.711124
7	0.056967	94.63036	0.225376	5.144264
8	0.063437	93.18448	0.185041	6.630478
9	0.069871	91.71968	0.166292	8.114028
10	0.076279	90.27658	0.167966	9.555458

Variance Decomposition of LHDI: Period	S.E.	LPCE	LHDI	LDSR
1	0.035773	13.06199	86.93801	0.000000
2	0.039197	22.28730	77.64485	0.067850
3	0.042122	32.56922	67.29813	0.132658
4	0.046635	42.84755	56.10464	1.047814
5	0.051512	51.65441	46.53613	1.809457
6	0.056433	58.58895	38.78388	2.627171
7	0.061692	63.66579	32.45504	3.879170
8	0.067175	67.37606	27.37534	5.248597
9	0.072754	70.07696	23.34331	6.579725
10	0.078431	71.94600	20.10788	7.946120

Variance Decomposition of LDSR: Period	S.E.	LPCE	LHDI	LDSR
1	0.390420	0.894307	1.424675	97.68102
2	0.465574	3.120476	1.259893	95.61963
3	0.501428	8.096601	1.204892	90.69851
4	0.546853	10.58720	3.081859	86.33094
5	0.586984	12.59934	3.957471	83.44319
6	0.617347	14.69119	4.038910	81.26990
7	0.643711	16.29792	4.353926	79.34815
8	0.667342	17.49770	4.697451	77.80484

9	0.687737	18.52296	4.852149	76.62489
10	0.705412	19.39099	4.970333	75.63868

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: LPCE LHDI LDSR

Variance Decomposition of LPCE: Period	S.E.	LPCE	LHDI	LDSR
1	0.014023	100.0000	0.000000	0.000000
2	0.021746	99.59311	0.278344	0.128542
3	0.029725	99.07437	0.506936	0.418699
4	0.036874	98.32989	0.434479	1.235626
5	0.043756	97.26550	0.355102	2.379394
6	0.050424	96.00230	0.286574	3.711124
7	0.056967	94.63036	0.225376	5.144264
8	0.063437	93.18448	0.185041	6.630478
9	0.069871	91.71968	0.166292	8.114028
10	0.076279	90.27658	0.167966	9.555458

Variance Decomposition of LHDI: Period	S.E.	LPCE	LHDI	LDSR
1	0.035773	13.06199	86.93801	0.000000
2	0.039197	22.28730	77.64485	0.067850
3	0.042122	32.56922	67.29813	0.132658
4	0.046635	42.84755	56.10464	1.047814
5	0.051512	51.65441	46.53613	1.809457
6	0.056433	58.58895	38.78388	2.627171
7	0.061692	63.66579	32.45504	3.879170
8	0.067175	67.37606	27.37534	5.248597
9	0.072754	70.07696	23.34331	6.579725
10	0.078431	71.94600	20.10788	7.946120

Variance Decomposition of LDSR: Period	S.E.	LPCE	LHDI	LDSR
1	0.390420	0.894307	1.424675	97.68102
2	0.465574	3.120476	1.259893	95.61963
3	0.501428	8.096601	1.204892	90.69851
4	0.546853	10.58720	3.081859	86.33094
5	0.586984	12.59934	3.957471	83.44319
6	0.617347	14.69119	4.038910	81.26990
7	0.643711	16.29792	4.353926	79.34815
8	0.667342	17.49770	4.697451	77.80484
9	0.687737	18.52296	4.852149	76.62489
10	0.705412	19.39099	4.970333	75.63868

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: LPCE LHDI LDSR