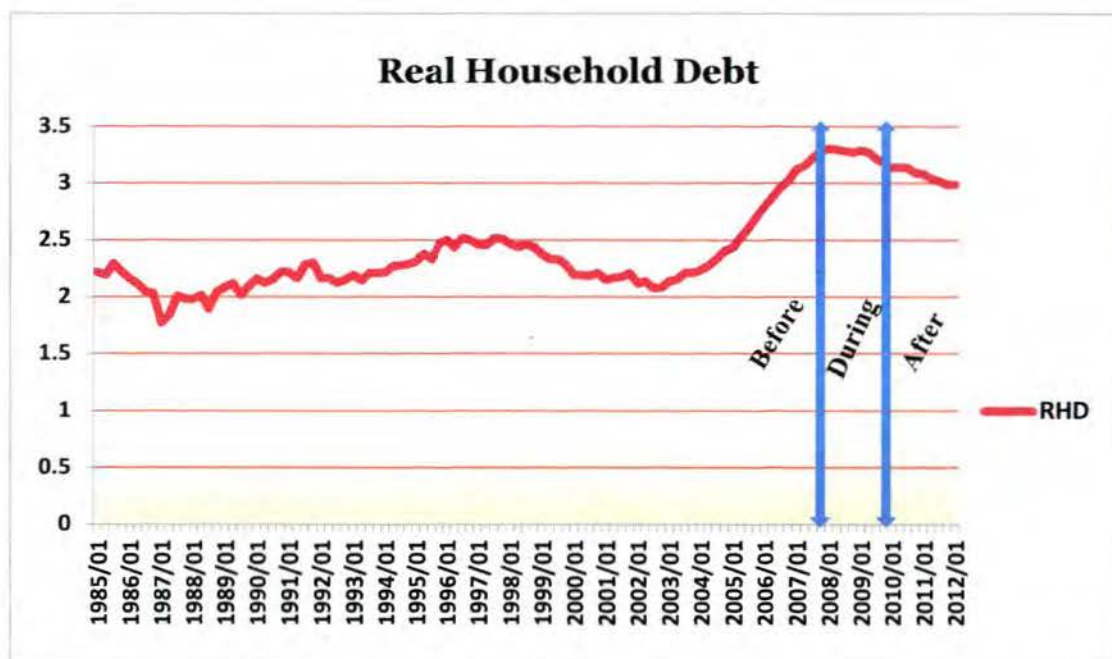


FINANCIAL CRISIS AND HOUSEHOLD INDEBTEDNESS IN SOUTH AFRICA: AN ECONOMETRIC ANALYSIS

CHRISTELLE MENIAGO, B.COM. HONS

23063106

Dissertation submitted in partial fulfilment of the requirements for the degree Magister Commercii (M.Com.) in Economics at the Mafikeng Campus of the North West University (NWU-MC)



Supervisor: Prof. Janine Mukuddem-Petersen (NWU-MC)

Co-Supervisor: Prof. Mark A. Petersen (NWU-MC)

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I dedicate this work to My Father Mr Gilbert Tekouenko and my Mother Mrs Françoise Tekouenko.

This dissertation has been the biggest challenge I have ever faced in my academic life. The acquisition of new skills, a tenacious character, analytical thinking and gaining invaluable experience are but a few of the many attributes that I have developed and enjoyed during this research endeavour.

I would like to acknowledge a few people who played a critical supportive role in enabling me to complete this dissertation.

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ABSTRACT

The 2007-2008 US subprime mortgage crisis evolved into a financial crisis that negatively affected many economies in the world and therefore it was widely referred to as the global financial crisis. Since the beginning of this financial crisis of 2008-2009, South Africa experienced a significant increase in its household debt to income ratio. In the main, the aim of this dissertation is to investigate the prominent factors contributing to the rise in the level of household debt in South Africa. Also, we study the response of household debt to various shocks originating from the aforementioned crisis. Additionally, in the context of our timeline (1985 Q1-2012 Q1) we will extrapolate possible graphical trends in the rise and fall of household indebtedness in South Africa associated with various crises. Working from past research papers and a theoretical framework developed by Franco Modigliani and Milton Friedman, seven macroeconomic variables will be considered to examine the rise of household borrowing to income namely; the real house price index, consumer price index, real income, real prime rate, real household consumption expenditure, real gross domestic product and real household savings. Both a long-run cointegration analysis and a short-run error correction model will be used to evaluate the relationship between household debt and the chosen variables by estimating a Vector Error Correction Model. Furthermore, the Variance Decomposition and the Generalized Impulse Response Function will be utilized to assess the impact of household debt to various shocks emanating from the 2008-2009 financial crisis. The different models and tests conducted in this research will be executed using the statistical software package EVIEWS 7. Based on the results, household debt was seen to have been fairly affected by the 2008-2009 financial crisis.

The cointegration analysis maintains that in the long run, household borrowing is positively and significantly determined by consumer price index and real household consumption. In addition, it confirms that household borrowing is negatively affected by real household income and real GDP. The rest of the variables were found insignificant. Nevertheless, the short run error correction model reveals that about 3.6% of the disequilibrium will be corrected each quarter for the equilibrium state to be restored. Also, the Variance Decomposition results confirmed that the South African household debt is mostly affected by shocks from real house price index, real household income, real household consumption and real household savings, respectively. Furthermore, the

Generalized Impulse Response Function results established the significant positive response of household debt to a shock from real house price index and real household consumption. The response of debt to shocks from consumer price index, real household savings and real income is negative and this outcome is confirmed by the theory.

However, the response of debt shows fluctuating behaviours to shocks from LRIN, LRPR and LRGDP over the estimated period.

In conclusion, our econometric investigation highlighted the main causes of the high levels of household debt in South Africa both in the short and long run. The Generalized Impulse Response Functions confirm that shocks like the occurrence of the 2007-2008 financial crisis will have a significant impact on real house price index, consumer price index, real household consumption and real household savings. The Engle granger results show that there exist no significant relationship between household debt and unemployment in South Africa over the period 1980 to 2010. However, we propose that this result may have been significant if quarterly unemployment data was available and included in the main data set. Finally, based on the stability, validity and reliability of our model, we recommend its use to facilitate policy analysis and decision making regarding household debt levels in South Africa.

Key Words: (Global) Financial crisis, Household indebtedness, Cointegration, Vector Error Correction Model, Variance Decomposition, Generalized Impulse Response Function, South Africa

PREFACE

One of the contributions made by the North-West University at Mafikeng (NWU-MC) to the activities of the financial economic community in South Africa has been the establishment of an active research group (FMORG) that has an interest in institutional finance, modelling and economic crises.

Under the guidance of Proffs. Mark A. Petersen and Janine Mukuddem-Petersen, this group has recently made valuable contributions to the existing knowledge about the modelling and optimization of financial institutions.

The work in this dissertation originated from our interest in Modelling, the 2008-2009 Financial crisis as well as household indebtedness in South Africa. From the onset it became apparent that little work has been done on this topic although it has been identified as an area of potential growth.

The outcomes of this project were collected in 6 research outputs which consist of 3 accepted chapters in a book entitled the “**Economics of Debt**”, published by NOVA in New York and 4 research articles submitted for possible publication.

DECLARATION

I, **Christelle Meniago**, hereby declare that apart from the assistance acknowledged, the original work contained in this dissertation for the degree of Master of Economics at the North West University (Mafikeng Campus) is my own. It has not been submitted before for any degree or its equivalence at this or any other university. I also declare that all secondary information used has been duly acknowledged in this dissertation.

Signature.....

Date.....

Christelle Meniago

The above declaration is confirmed by:

Signature.....

Date.....

Supervisor

Signature.....

Date.....

Co-supervisor

CERTIFICATE OF ACCEPTANCE FOR EXAMINATION

This dissertation entitled “**Financial Crisis and Household Indebtedness in South Africa: An Econometric Analysis**”, submitted by **Christelle Meniago**, student number **23063106** of the Department of Economics in the Faculty of Commerce and Administration is hereby recommended for acceptance for examination.

Signature.....Date.....

Supervisor: Prof. Janine Mukuddem-Petersen
Department: Graduate School of Business and Government Leadership
Faculty: Commerce and Administration
University: North West University (Mafikeng Campus)

Signature.....Date.....

Co-supervisor: Prof. Mark A Petersen
Department: Office of the Dean
Faculty: Commerce and Administration
University: North West University (Mafikeng Campus)

TABLE OF CONTENTS

ACKNOWLEDGMENTS.....	i
ABSTRACT	iii
PREFACE.....	v
DECLARATION	vi
CERTIFICATE OF ACCEPTANCE FOR EXAMINATION.....	vii
LIST OF ACRONYMS.....	xii
LIST OF TABLES	xiii
LIST OF FIGURES.....	xiv
APPENDICES	xv
GLOSSARY OF TERMS.....	xvi
CHAPTER 1.....	1
ORIENTATION OF THE STUDY	1
1.1 INTRODUCTION	1
1.2 PROBLEM STATEMENT	5
1.3 AIMS AND OBJECTIVES.....	6
1.3.1 Aims	6
1.3.2 Objectives.....	6
1.4 RESEARCH QUESTIONS AND HYPOTHESIS.....	8
1.4.1 Research Questions	8
1.4.2 Hypothesis.....	8
1.5 SIGNIFICANCE OF THE STUDY	9
1.6 LIMITATIONS/DELIMITATIONS	9
1.7 STRUCTURE OF DISSERTATION.....	9
CHAPTER 2.....	11
LITERATURE REVIEW	11
2.1 INTRODUCTION	11

2.2	THEORETICAL FRAMEWORK.....	12
2.2.1	The Life-Cycle Hypothesis (LCH).....	13
2.2.2	The Permanent-Income Hypothesis (PIH)	17
2.3	MEASUREMENT OF HOUSEHOLD DEBT	21
2.3.1	Household Debt to Disposable Income Ratio	21
2.3.2	The Debt Service Ratio	21
2.3.3	The Debt to Asset Ratio	21
2.4	CONSEQUENCES OF INCREASING HOUSEHOLD DEBT	22
2.5	COMPOSITION OF HOUSEHOLD DEBT IN SOUTH AFRICA.....	23
2.5.1	Mortgage Debt	23
2.5.2	Consumer Credit	23
2.6	REVIEW OF THE EMPIRICAL LITERATURE	25
 CHAPTER 3.....		36
DATA AND METHODOLOGY.....		ERROR! BOOKMARK NOT DEFINED.
3.1	INTRODUCTION	36
3.2	MODEL SPECIFICATION.....	36
3.3	DATA DESCRIPTION.....	38
3.4	MODELLING STRATEGY	41
3.4.1	Gathering of the Variables	45
3.4.2	Log Transformation of the Variables	45
3.4.3	Descriptive Statistics.....	45
3.4.4	Visual Inspection and Stationarity	45
3.4.6	Determination of the lag structure.....	54
3.4.7	Cointegration.....	55
3.4.8	Estimation of the Vector Error Correction Model	59
3.4.9	Diagnostics and Stability Tests	61
3.4.10	Variance Decomposition Analysis.....	65

3.4.11	Generalized Impulse Response Functions.....	66
CHAPTER 4.....	68	
EMPIRICAL RESULTS AND INTERPRETATION	68	
4.1	INTRODUCTION	68
4.2	DESCRIPTIVE STATISTICS	69
4.3	VISUAL INSPECTION OF THE VARIABLES	71
4.4	STATIONARITY TEST.....	75
4.4.1	The ADF test.....	76
4.4.2	The PP test	78
4.4.3	The KPSS test	80
4.5	LAG LENGTH DETERMINATION TEST	82
4.6	JOHANSEN COINTEGRATION TEST	83
4.7	ESTIMATION OF THE VECTOR ERROR CORRECTION MODEL	89
4.7.1	Long run exclusion test.....	90
4.7.2	Weak exogeneity test	91
4.8	DIAGNOSTIC TESTS.....	92
4.8.1	Autocorrelation test.....	92
4.8.2	Heteroskedasticity Test.....	93
4.8.3	Normality Test	94
4.8.4	Stability Test of the VECM.....	94
4.9	DISCUSSION OF THE RESULTS	95
4.10	DYNAMIC ANALYSIS OF THE VECM	98
4.10.1	Variance Decomposition.....	98
4.10.2	Generalized Impulse Response Function (GIRF)	100
4.11	RELATIONSHIP BETWEEN HOUSEHOLD DEBT AND UNEMPLOYMENT USING ANNUAL DATA	104
4.11.1	The stationarity test.....	105

4.11.2	Testing for cointegration	106
CHAPTER 5.....		111
CONCLUSIONS AND RECOMMENDATIONS		111
5.1	INTRODUCTION	111
5.2	CONCLUSION OF RESULTS	112
5.3	RECOMMENDATIONS.....	114
5.4	FUTURE RESEARCH.....	117
BIBLIOGRAPHY		118
APPENDICES		134

LIST OF ACRONYMS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
CE	Cointegrated equations
CPI	Consumer Price Index
ECM	Error Correction Model
GIRF	Generalised Impulse Response Function
HQ	Hannah-Quinn Information criterion
IRF	Impulse Response Function
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LCH	Life-cycle Hypothesis
LM	Lagrange Multiplier
LCPI	Log of Real Consumer Price Index
LRCON	Log of Real Consumption Expenditures
LRGDP	Log of Real Gross Domestic Product
LRHD	Log of Real Household Debt
LRHPI	Log of Real House Price Index
LRIN	Log of Real Income
LRPR	Log of Real Prime Rate
LRSV	Log of Real Savings
NCA	National Credit Act
OECD	Organization for Economic Corporation and Development
OLS	Ordinary Least Squares
PIH	Permanent Income Hypothesis
PP	Phillips-Perron
SA	South Africa
SARB	South African Reserve Bank
SIC	Schwarz Information criterion
SMC	Subprime Mortgage Crisis
Stats.sa	Statistics South Africa
VAR	Vector Autoregression
VECM	Vector Error Correction Model

LIST OF TABLES

Table 2.1:	Possible Expected Signs of the Variables
Table 2.2:	Comparison of Methodologies
Table 2.3:	Analysis of Selected Literature to Compare the Number of Observations
Table 3.1:	Summary of Data Description
Table 3.2:	Information Criteria Selection
Table 4.1:	Summary of the Descriptive Statistics of the Variables
Table 4.2:	ADF Unit Root Test Results
Table 4.3:	PP unit root test results
Table 4.4:	KPSS unit root test results
Table 4.5:	Lag length determination criteria results
Table 4.6:	Cointegration test results
Table 4.7:	Unrestricted cointegrating coefficients
Table 4.8:	Automatic normalized cointegrating coefficients
Table 4.9:	Normalized cointegrating equations
Table 4.10:	VECM results
Table 4.11:	Long-Run exclusion test results
Table 4.12:	Weak exogeneity test results
Table 4.13:	VEC residual serial correlation LM test results
Table 4.14:	VEC Heteroscedasticity test (No cross terms) results
Table 4.15:	Normality test results
Table 4.16:	Variance Decomposition of Household Debt
Table 4.17:	ADF and PP test results
Table 4.18:	Long run equation
Table 4.19:	ADF test results on residuals
Table 4.20:	PP test results on residuals
Table 4.21:	Engle granger critical values

LIST OF FIGURES

- Figure 1.1:** Level of Household Debt to Income Ratio in Selected Countries
- Figure 3.1:** Steps for Estimating a VECM for Household Debt
- Figure 3.2:** Steps of the Engle-Granger approach
- Figure 4.1** Graphical analysis of household debt
- Figure 4.2:** Graph of variables at their level
- Figure 4.3:** Graph of variables at their first difference
- Figure 4.4:** Stability test of VECM
- Figure 4.5:** Response to Generalized one S.D. Innovations
- Figure 4.6:** Response to Generalized One S.D. Innovations
- Figure 4.7:** Graphical Inspections of the Series at Level and First Difference
- Figure 4.8:** Graph of residuals

APPENDICES

Appendix A: Johansen Cointegration Test

Appendix B: VECM Estimates with One Equation

Appendix C: VECM estimates with two equations

Appendix D: Portmanteau Autocorrelation test

Appendix E: VEC Residual Heteroskedasticity test (No cross terms)

Appendix F: VEC Residual Normality test

Appendix G: Variance Decomposition

Appendix H: GIRF Results

GLOSSARY OF TERMS

Cointegration is a situation where if two or more series are individually integrated but some linear combination of them has a lower order of integration, then the series are said to be cointegrated.

Error-correction model is a dynamic model in which the movement of the variables in any periods is related to the previous period's gap from long-run equilibrium.

Financial Crisis refers to an economic scenario where the economies of countries all over the world are facing a liquidity crunch and taking steps forward to combat this issue. The financial crisis of 2008-2009 commonly referred as the global financial crisis refers to the global credit, banking, currency, and trade crisis which emerged in September 2008.

Generalized Impulse Response Function is an analysis used to construct the time path of the dependent variables in the vector autoregressive model to shocks from all the independent variables.

Household indebtedness is the debt acquired by individuals for personal use.

Household savings is the difference between a household's disposable income and its consumption. The household saving rate is calculated by dividing household saving by household disposable income.

Household debt to disposable income is the ratio between a person's income and how much they pay monthly in instalments and revolving debt.

Life-Cycle Hypothesis is an economic theory developed by Franco Modigliani that relates to the spending and saving behaviour of people over the course of a lifetime.

Permanent Income Hypothesis is an economic theory developed by Milton Friedman which declares that people will consume based on their expected long term income. The level of their expected long term income then becomes thought of as the level of permanent income that can safely be spent.

Prime overdraft rate is a reference interest rate commercial banks use when issuing variable interest rate loans to their customers. The prime overdraft rate can also be referred to as prime rate.

Stochastic process is simply a collection of random variables indexed by time whose behaviour is non-deterministic. The random variables are generally known as time series. In simpler terms, a stochastic process is simply a probability process; that is any process in nature whose evolution can be analysed successfully in terms of probability.

Vector Error Correction Model is an econometric technique used in the estimation of the long-run and short-run equilibrium parameters in a relationship with non-stationary variables.

CHAPTER 1

ORIENTATION OF THE STUDY

"Always live within your income, even if you have to borrow money to do so."

Billings, Josh

"Credit is a system whereby a person who cannot pay gets another person who cannot pay to guarantee that he can pay."

Dickens, Charles

- 1.1. INTRODUCTION
- 1.2. PROBLEM STATEMENT
- 1.3. AIMS AND OBJECTIVES
- 1.4. RESEARCH QUESTIONS AND HYPOTHESIS
- 1.5. SIGNIFICANCE OF THE STUDY
- 1.6. LIMITATIONS/DELIMITATIONS
- 1.7. STRUCTURE OF DISSERTATION

1.1 INTRODUCTION

The world suffered from several crises since the year 1970. According to Laeven and Valencia (2012), the world records in total 147 banking crises over the period 1970-2011. Nonetheless, we identify the three most recent important crises which affected many economies in the world. We note the US Subprime Mortgage Crisis (SMC) of 2007-2008, the 2008-2009 financial crisis and the recent European sovereign debt crisis. Notwithstanding the importance of all these crises, our main focus will be based on the 2008-2009 financial crisis.

The US Subprime Mortgage Crisis (SMC) which started in 2007-2008 is considered by many economists to be the most significant incident since the great depression of the 1930's. Petersen *et al.* (2012) indicated that the SMC shook the foundations of the financial industry

by causing the failure of many iconic Wall Street investment banks and prominent depository institutions. This crisis stymied credit extension to households and businesses thus creating credit crunches and, ultimately recessions. In this regard, Petersen *et al.* (2012) formulated the IDIOM hypothesis which highlights the main causes of the SMC to be largely caused by the intricacy and design of subprime mortgage origination, securitization and agents that led to information problems and valuation opaqueness. In addition, several experts in the field concluded that the SMC was not mainly caused by over lending of banks, but instead by risky lending (referred to as subprime lending).

In mid-2008-2009, the SMC cascaded into a financial crisis that spread to some regions of the world. Allen and Giovannetti (2011) accentuated that the seeds of this crisis can be traced to the low interest rate policies adopted by the Federal Reserve Bank and other central banks after the collapse of the technology stock bubble. Initially, the crisis was commonly referred to as the global financial crisis (GFC) but later on debate arose about the countries actually affected. Presently, it is principally claimed to be a US and European crisis because of the intense injury to US and European industries especially in the banking, insurance and housing sectors. In particular, with the onset of the crisis, the US and European banks experienced debtors incapacity to service their agreements on time and, consequently, credit to households became of great concern to financial institutions and policy makers alike. The household sector was identified as having a very low savings rate and in turn household indebtedness has escalated significantly. According to Masilela (2009) the financial crisis is to a large extent a debt crisis.

Due to contagion, the crisis spread and affected several countries in the world to varying degrees. For instance, Naude (2009) emphasized that the overall effects of the financial crisis on developing countries and especially African countries will certainly be negative. Specifically, the author asserted that some countries will be more negatively affected especially those dependent on trade with the United States, countries having large fiscal deficits and eventually those with poorly regulated financial sectors. The SMC accompanied by the 2008-2009 financial crisis represented a severe assault for African economies because it basically befell at a period when the economies were producing some improvement in their economic performances. Nevertheless, several economists believed that many emerging economies could overcome the crisis. In this context, it was initially postulated that financial institutions in South Africa would not suffer too much from the debt crisis because of its little

inclusion in the global economy and insignificant exposure to the US sub-prime mortgage market as compared to European banks. However, Economists foreseen that Africa would be slightly more affected due to the fact that several African banks are controlled by overseas economies. Due to the spill-over effects of the crisis, many industrialised and developing countries began to feel the effects of the financial crisis in varying degrees. These effects included the considerable devaluation of assets, tightening of financial conditions, shut down of companies, rise in unemployment and a slow-down of economic growth.

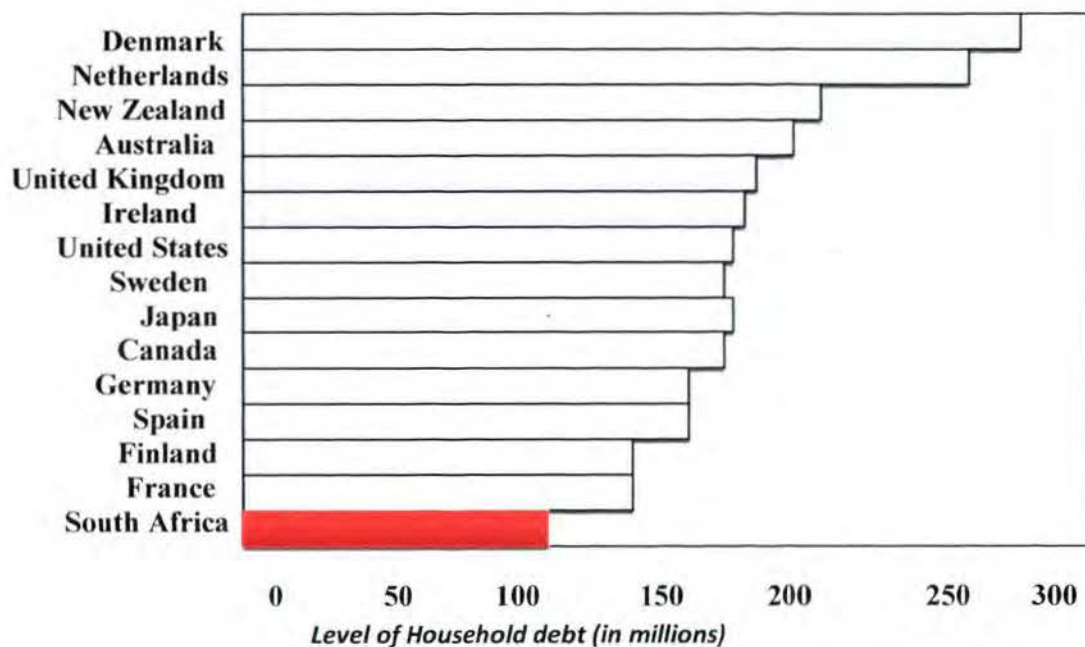
Notwithstanding the initial assumptions about South Africa not being affected significantly by this crisis, this economy was plunged into a recession for the first time in 17 years. South Africa started experiencing a decline in its economic growth, employment, investment as well as the income of households. Characterized as a middle class economy, South Africa has long standing structural problems like high rate of poverty, unemployment followed by the highest income inequality in the world. In this manner, South Africa is known for recording negative levels of savings in the personal and government sectors but most especially in the household sector. This low savings level contributed to a persistent structural weakness in South Africa (Aron & Muellbauer, 2000a) and is the basic cause of South Africa's behaviour of borrowing. This condition of low savings rate even got worse during the crisis which led to a high percentage of debt in the household sector.

In South Africa, like in many other countries, most of the households acquire debt in their daily lives. They purchase non-durable commodities on their credit cards and most often take a loan from the bank to purchase durable goods like houses and cars. However, they sometimes find it very difficult to repay these loans. Financial institutions in South Africa, as in many other countries, are acknowledged to be the primary source of credit to households and for that reason we affirm that the majority of their debt comes as a result of borrowings from banks. Greater access to credit makes it easier for households to spend. This easy access to credit encourages consumers to purchase immediately rather than in the future. According to the data from the South African Reserve Bank (SARB), total credit extended to the private sector by money lenders have become very high in recent years. In 2003, credit extended to the private sector was R 378 530 million and has increased rapidly from R 867 635 million in 2007 to R1 102 005 million in 2010. For instance, increasing demands for new vehicles are one of the durable goods associated with this increase in household debt. According to NAAMSA (National Association of Automobile Manufacturers of South Africa), an

independent statistical service provider, the aggregate domestic sales of new cars significantly increased in recent years. This insensitive borrowing has encouraged households to go into more debt and caused a significant increase in South African debt to income ratio. Consequently, government intervention in the form of the National Credit Act of 2005 came into effect on 1 June 2007 and fundamentally focused on protecting consumers against over-indebtedness, exploitation and manipulation by the informal sector.

Consequently, the high debt level incurred by the household sector has created economic and political concern in many developed as well as developing countries in the world. Figure 1.1 compares the level of household debt to disposable income ratio in several countries.

Figure 1.1: Level of Household Debt to Income Ratio in Selected Countries



Source: OECD and SARB (as cited in Kevin Lings and Laura Jones, 2010)

From Figure 1.1, we noticed that even the most influential economies in the world record very high debt levels compared to South Africa. The ratio of household debt to disposable income has briskly augmented in recent years in both Denmark and the Netherlands. In contrast, France alongside with Finland did not experience such significant increases as compared to those other countries. Although high, South Africa has a very good household

debt to income ratio compared to the biggest economies in the world. These big economies are interconnected with the US economic and financial system, and therefore, it can be concluded that the increase in their debt to income ratios was primarily due to the US economic recession of 2007-2008. Presently, the high debt ratios can be explained by the continuing adverse effects of the 2008-2009 financial crisis and the arrival of the European sovereign debt crisis.

Nevertheless, within the context of South Africa, debt remains at historically high levels. Generally, several authors studied the impact of the financial crisis in Africa while some gave special attention to the Southern Africa region. However, little studies considered studying the impact of the financial crisis on a selected economy using an extensive econometric approach.

1.2 PROBLEM STATEMENT

For an economy to be in a good financial situation, the household sector must record low debt levels. To reach this goal, the banks must be very prescriptive and discerning when it comes to the provision of loans to customers. Unfortunately, South Africa records a very high debt level. According to the SARB quarterly bulletin (June 2012), the ratio of household debt to disposable income decreased slowly to 74.7% in the first quarter of 2012 compared to 74.8% in the fourth quarter of 2011. Though this is seen as a slow decrease, this figure still remains very high and such high levels of household debt may have adverse effects on the economy. With escalating debt, the household sector may run the risk of being too exposed to several adverse surprises like unemployment shocks, asset price shocks and shocks from income, just to name a few. On the other hand, with a considerable level of debt in the household sector, the economy is also protected against unpleasant consequences.

Historically, financial crunches emanate devastating shocks to vulnerable economies. Without an effective investigation to discover what might cause this high level of debt in South Africa, the household sector might still remain very susceptible to shocks. In lieu of this, our main attention focuses on the 2008-2009 financial crisis and its impact on the household indebtedness in South Africa. An extensive econometric investigation will help ascertain which variables contribute to the rising indebtedness and which shocks significantly impact the South African economy. Consequently, measures can then be proposed to alleviate credit conditions thereby encouraging a stable financial household sector in South Africa.

1.3 AIMS AND OBJECTIVES

1.3.1 Aims

Few empirical studies have attempted to explain why household debt in South Africa still remains at a very high level. Similarly, contributions have been made to define the different potential explanatory factors causing increasing household debt levels in the country. Therefore, the major aims of this dissertation are:

1.3.1.1 To identify the parameters related to the 2008-2009 financial crisis and to analyse how the South African household debt levels are affected before, during and after this crisis.

1.3.1.2 To investigate the main determinants of the high level of household debt in South Africa.

1.3.1.3 To design an econometric model for household debt in South Africa for the period 1985 Q1 to 2012 Q1. In particular, to discover the relationship that exists between household debt and other macroeconomic determinants as well as other related variables.

1.3.1.4 To describe the relationship between household debt and unemployment in South Africa

1.3.1.5 To consider the impact of various shocks to household debt in South Africa and to overcome the shortcomings of other papers in this regard.

1.3.1.6 To formulate some suggestions pertaining to how South Africa's household debt can be reduced to a reasonable level.

1.3.2 Objectives

The objectives of our study include:

1.3.2.1 The critical screening of literature related to the 2008-2009 financial crisis in developing countries and the identification of those parameters related to household

indebtedness. A graphical analysis of possible trends in the South African level of household indebtedness in relation to the periods “before”, “during” and “after” the aforementioned crisis.

1.3.2.2 Considering related studies and economic theory to help identify the determinants that affect household indebtedness in South Africa.

1.3.2.3 Using time series data and the application of the Vector Error Correction Model (VECM) to analyse the long-run and short-run relationship between household debt and its main determinants during the period 1985 Q1-2012 Q1.

1.3.2.4 Using the Engle-Granger approach to describe the relationship between unemployment and household debt in South Africa from the period 1980-2011.

The unemployment variable is considered to be a very important factor related to the high debt levels in the household sector. However, in lieu of the fact that South Africa started publishing quarterly unemployment data since 2008, it is impossible for us to take in this variable in the main data set as it includes quarterly data from 1985. Therefore, due to its importance, a separate Engle-Granger test will be used to estimate the relationship between household debt and unemployment, using annual data from the period 1980-2011.

1.3.2.5 To use the Generalized Impulse Response Function (GIRF) to evaluate the impact of shocks on the level of South African household indebtedness. Also, to use the Variance Decomposition analysis to evaluate which variables mostly contribute in explaining the shocks in household debt.

1.3.2.6 Utilizing the econometric results to formulate some recommendations to decrease South Africa’s household debt level.

1.4 RESEARCH QUESTIONS AND HYPOTHESIS

1.4.1 Research Questions

Question 1.4.1.1: *What are the parameters related to the 2008-2009 financial crisis and what is the level of South African household debt before the onset, during and after the period of the aforementioned crisis?*

Question 1.4.1.2: *What are the main determinants why most South African households enter into debt?*

Question 1.4.1.3: *What are the main explanatory factors regarding the relationship between household debt and other macroeconomic determinants?*

Question 1.4.1.4: *What is the relationship between household debt and unemployment?*

Question 1.4.1.5: *What is the response of household debt in South Africa to the 2008-2009 financial crisis shock?*

Question 1.4.1.6: *What measures can be taken in South Africa to reduce household debt at a reasonable level?*

1.4.2 Hypothesis

In this study, we hypothesized that the financial crisis of 2008-2009 will have a negative impact on the level of household indebtedness in South Africa. We therefore present our hypotheses as follows:

H_0 : The financial crisis will negatively effect on the level of household debt in South Africa.

H_1 : The financial crisis will positively effect on the level of household debt in South Africa.

1.5 SIGNIFICANCE OF THE STUDY

This study is important because:

1.5.1 To the best of our knowledge, this study is the first of its kind to conduct a detailed econometric analysis to investigate the main reasons why South African households enter into debt and records high debt levels in their balance sheet.

1.5.2 Our contribution to the available literature on South African household debt levels response to the advent of the 2008-2009 financial crisis through a GIRF analysis will be novel.

1.5.3 For the first time, the variables that mainly contribute to the high levels of household debt in South Africa will be identified by utilizing the Variance Decomposition econometric test.

1.6 LIMITATIONS/DELIMITATIONS

Presently, limitations may include the availability and access to data.

The availability of quarterly unemployment data for the entire period is a limitation, however, we can try and study a selected period using annual data that is available and this will then be a delimitation.

1.7 STRUCTURE OF DISSERTATION

This dissertation will consist of the following chapters:

CHAPTER 1: ORIENTATION OF THE STUDY

CHAPTER 2: LITERATURE REVIEW

CHAPTER 3: DATA AND METHODOLOGY

CHAPTER 4: EMPIRICAL RESULTS AND INTERPRETATION

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

Chapter 1 consists of the introductory chapter. This chapter provides a detail explanation of the aims and objectives, problem statement, research questions and hypothesis, significance and limitations/delimitations of the study. Chapter 2 is the literature review and it presents both theoretical and empirical literature in relation to this study. It also includes a critical evaluation of previous research and how it relates to our study. In Chapter 3, a detailed explanation of the evaluation techniques implemented in this study is provided. The chapter specifies our model aligned with the theoretical framework and some relevant empirical studies. Moreover, the source and definition of the variables used are explained in detail. Chapter 4 provides the estimation results of the different tests conducted in the previous chapter followed by their interpretation while Chapter 5 concludes the study. The next section contains the bibliography with all the articles, dissertations and books surveyed in this dissertations followed by the list of appendices.

CHAPTER 2

LITERATURE REVIEW

I'm living so far beyond my income that we may almost be said to be living apart.

E. E. Cummings (1894-1962)

2.1. INTRODUCTION

2.2. THEORETICAL FRAMEWORK

2.3. MEASUREMENT OF HOUSEHOLD DEBT

2.4. CONSEQUENCES OF INCREASING HOUSEHOLD DEBT

2.5. COMPOSITION OF HOUSEHOLD DEBT

2.6. REVIEW OF THE EMPIRICAL LITERATURE

2.1 INTRODUCTION

In this chapter, we survey the existing literature seeking to address the impact of the financial crisis of 2008-2009 on household indebtedness in South Africa. We searched both the theoretical and empirical literature. The theoretical framework of this research serves as a guide when selecting the variables to be measured. Also, it facilitates this research in estimating the statistical relationship of the variables in order to construct our model. In lieu of our real data observations, we will be able to test if the hypothesis proposed by the theoretical model will hold in our case. On the other hand, we review the empirical literature of existing studies on the subject. Specifically, we investigate the determinants of household debt and other research related to the aforementioned crisis. Also, we consider the body of literature which investigates the impact of shocks on related variables using the Generalized Impulse Response Function (GIRF).

2.2 THEORETICAL FRAMEWORK

Philbrick & Gustafsson (2010) affirmed that the two reasons why households take on large amount of debt are to smooth their expenditures and to finance the purchase of resources. When surveying the available literature, it is evident that the two major theories explaining the consumption smoothing of households and why they go in for debt are the life-cycle model and the permanent income model. In the sequel, we highlight theories such as the Keynesian model which led to the development of the two aforementioned theories. In 1936, Keynes presented a study to demonstrate the relationship between consumption and national income. In this context, he postulates that as income rises, consumers will save a bigger fraction of their income. Also, he maintains that as consumption of households increases, their income will also increase although the increases in consumption will not be as great as the increase in income (http://en.wikipedia.org/wiki/consumption_function). Keynes considers that the marginal propensity to consume (MPC)¹ plays a central role in the Keynesian theory and in the main identifies what the household sector does with its extra income. Additionally, he proposed that the Average Propensity to Consume (APC)² measures the percentage of income spent on goods and services rather than on savings. Finally, Keynes concluded that income is the primary determinant of consumption.

Keynes consumption function is described as follows:

$$C = a + bY \quad (2.1)$$

Where **C** represents the consumption spending by households

a represents autonomous consumption

b is the marginal propensity to consume (MPC)

Y is the disposable income

From equation (2.1), Keynes advocated that current consumption depends only on current income. Based on the Keynesian model, several economists predicted that consumption would grow more slowly than income over time. However, supported by different studies,

¹MPC is the proportion of each additional dollar of household income that is used for consumption expenditures.

² APC is the ratio of consumption to income.

this prediction did not actually come true. It was seen that as income grew, consumption also grew at the same rate. As a result of the Keynesian theory, the theories of the Life-Cycle Hypothesis (LCH) and the Permanent-Income Hypothesis (PIH) were developed to explain the saving and borrowing behavior of households.

2.2.1 The Life-Cycle Hypothesis (LCH)

Before analysing the determinants of household indebtedness in South Africa, we consider the life-cycle model of consumption. This model serves as our base model when selecting our variables. The LCH is an economic concept evaluating individual consumption patterns. It was first formalized by the economists Irving Fisher, Rod Harrod, Albert Ando and Franco Modigliani, but it mainly originated from the latter. This concept of the LCH is contradictory to the Keynesian consumption theory. While the latter is based on the current income of the individuals, the LCH says that the individual consumption is directly based on consumer tastes, preferences and income. Modigliani's LCH is mostly based on the hypothesis that:

- i. Income varies thoroughly over a lifetime of an individual.
- ii. Consumers use savings and borrowing to smooth their consumption.
- iii. Consumption depends on wealth and income.

In other words, Modigliani formulated that income will vary over people's lives and that savings allow consumers to move income from those times in life when income is high to those times when income is low. Hence, we can conclude that Modigliani's model is known for its well-built argument that savings is positive in the working age of the households and negative when they are retired. Modigliani and Ando argue that the average propensity to consume is larger in the old households and among young people. This hypothesis thus created a model of saving behaviour emphasizing the individual.

The model assumes that a household can maximize utility over its life-time subject to an intertemporal budget constraint. This implies that by smoothing their consumption, households can maximize utility over their life-cycle. Clearly, the model can foresee that consumption in each period is dependent on expectations about life time income. Assuming that household income is upward sloping, we can say that during the early stage of their

working life, households will have a negative saving rate. However, as they will grow older together with their income, indebtedness will decrease. Upon retirement, that is when households are no longer working, households will again dissave as in the early stage of their working life. Households may then enter into debt in periods when their income is extremely low, mainly because they need to finance their existing consumption. Households will then repay these loans in periods when their income will be relatively high. Therefore, at this stage of their lives (retirement age), their consumption is mostly financed by the income they earned during their working age. We conclude that the LCH shows a negative relationship between household indebtedness and real income.

In summary, the LCH examined the saving/borrowing behaviour of individuals who reduced their consumption over their lives by accruing savings during their producing years and preserving consumption levels during retirement. Mankiw (2007) describes the basic model of a LCH as follows:

The basic model:

W = initial wealth

Y = annual income until retirement (assumed constant)

R = number of years until retirement

T = lifetime in years

The assumptions of the model are described as:

1. Zero real interest rate (for simplicity)
2. Consumption-smoothing is best

➤ Lifetime resources = $W + RY$

➤ To achieve smooth consumption, consumer divides his/her resources equally over time:

$$C = (W + RY)/T \quad (2.2)$$

Or

$$C = aW + bY \quad (2.3)$$

where

$a = (1/T)$ is the marginal propensity to consume out of wealth

$b = (R/T)$ is the marginal propensity to consume out of income

From equation (2.2), Modigliani assumes that there is a consumer who expects that he will live for another T years and has wealth of W . The consumer also expects to earn income Y until he retires R years from now. In this situation the consumer's resources over his lifetime consists of his initial endowment of wealth, W and his lifetime earnings of RY . It has to be added that we are assuming that the interest rate is zero. If the interest rate was positive, we would have to account for the interest earned on savings.

The LCH can therefore solve the consumption puzzle:

- The life-cycle consumption function implies

$$APC = C/Y = a(W/Y) + b \quad (2.4)$$

- Across households, income varies more than wealth, so high-income households should have a lower APC than low-income households.
- Over time, aggregate wealth and income grow together, causing APC to remain stable.

Evidently, the outcome of the LCH is that current consumption is based on lifetime labour-income (human-wealth) and non- labour income (non-human wealth). This contrasts with the Keynesian consumption function which states that current consumption is strongly related to current disposable income (<http://www.investopedia.com/terms/l/life-cycle-hypothesis.asp>). It is therefore possible to say at this stage that the indebtedness of a household is influenced by its future income.

The LCH model also sustains the role of housing and its great influence in the spending choice of households. Households often enter into large amounts of debt to finance big assets like cars or houses. Housing is relatively high because the cost of acquiring a house is also high. This constitutes a big determinant why households enter into debt. In South Africa for example, house prices kept on increasing in recent years. The LCH framework therefore concludes that increasing house prices will lead to an increase in current and future consumption thereby causing household debt levels to be high.

Likewise, interest rates play a big role in the sense that it affects the cost of borrowing. The theory does not really present a definite conclusion about the expected effect of the changes in interest rate on either savings or consumption. The model foretells that a high level of interest rate will encourage savings, implying that if interest rates are low, the savings rate will fall and will eventually decrease the cost of borrowing thereby encouraging households to borrow. This situation is known as the substitution effect. Another situation may arise where a fall in interest rates will leave households with a limited amount of money in their pockets. Less money will imply a decrease in their consumption and increase in savings. This type of situation is known as the income effect. Nevertheless, the concept of decreasing interest rates causing an increasing debt to income ratio has been widely accepted in literature and will be used as one of the basis in this dissertation.

Household debt to disposable income ratio is also influenced by a strong variable, namely inflation. We explored the effects of inflation on savings and debt through the role it plays in affecting interest rates. A lower rate of inflation may result in a lower growth of nominal household income and when inflation is high the initial loan repayment is higher (Debelle, 2004). This situation can therefore be summarized in the sense that lower inflation rates will lead to a decrease in the interest rate which in turn will cause household debt to escalate. According to Debelle (2004), lower inflation rates will have two effects on the debt-to-income ratio. Firstly, lower inflation will cause a decline in the nominal interest rates and this situation will boost the numerator because of increased borrowing by the household sector. Secondly, the lower inflation rate will lower the growth of nominal household income. As a result, the nominal value of the debt will erode more slowly thereby boosting the debt to income ratio. In simpler terms, the LCH advocates that as inflation rates are lower, household debt will increase since the cost of borrowing will also be made lower.

Based on the LCH, economic growth has its role to play in the level of household debt. Higher economic growth means higher income enjoyed by the household sector, creation of jobs, and more especially consumer confidence. In a country where economic growth reaches higher levels, banks will be more secure and less constrained about issuing credit to the households. This situation of higher economic growth will increase the future expectations of households and will consequently boost their self-assurance level on taking on credit. We then terminate that the LCH envisages that higher economic growth leads to higher debt.

The age structure of the population also plays a great role in examining the level of debt in an economy. The LCH model articulates that if the population of a country is mostly composed of younger households, then the level of household debt will be very high compared to the case where we are dealing with a greater proportion of older households. The LCH suggests that it is necessary to save money during the early ages to be able to provide for retirement. Modigliani later explained that the LCH is a theory about individual and aggregate wealth meaning that the young population has little wealth, the middle-age individuals will possess more while people at their retirement age will possess very little.

2.2.2 The Permanent-Income Hypothesis (PIH)

One of the most important messages on PIH is that households look at the future on deciding on their current consumption.

The PIH is an economic theory developed by the economist Milton Friedman in 1957 to explain consumer behaviour. Friedman's PIH is a complement of the LCH of Franco Modigliani. In particular, Friedman argues that consumption should not depend on current income alone. This model emphasizes that consumers use saving and borrowing behaviour to smooth their consumption in response to random and temporary changes in their incomes from year to year. In other words, Friedman says that the primary determinant of current consumption is not current income but what he called "permanent income"³. This theory just says that transitory, short-term changes in income have little effect on consumer spending behaviour. In this model, the fundamental determining factor of consumption is not the

³Friedman states that individual consumption is not determined by current income but by the longer-term income expectations. The longer-term income expectation is what he referred to as the "*permanent income*".

individual's real disposable income but its real wealth. Mankiw (2007) defines Friedman's basic model as follows:

$$Y = Y^P + Y^T \quad (2.5)$$

where

Y = current income

Y^P = permanent income: average income, which people expect to persist into the future

Y^T = transitory income: temporary deviations from average income

From the basic model, we see that Friedman suggested that we actually view the current income Y as the sum of two components, permanent income Y^P and transitory income Y^T .

Nevertheless, the PIH can also solve the consumption function

$$C = a Y^P \quad (2.6)$$

Where a is the fraction of permanent income that people consume per year.

The PIH solves the consumption puzzle and implies that

$$APC = C / Y = a Y^P / Y \quad (2.7)$$

This equation means that if high-income households have higher transitory income than low-income households, APC is lower in high-income households. However, it says in the long-run that income variation is due mainly (if not solely) to variation in permanent income, which implies a stable APC (Mankiw, 2007).

Milton Friedman came to the conclusion that the individual will consume a fixed proportion of his/her permanent income. The individual's permanent income is determined by the assets he possess, both physical (shares, bonds, property) and human (education). Transitory income, however, is the difference between the measured income and the permanent income. The idea behind this model is straightforward in that individual consumption is based on their 'permanent income', that is the income they expect to earn over a considerable period of time.

The two theories discussed above, that is the LCH and PIH, both have the universal idea that households try to smooth their expenditures in the face of changing current income. In other words, both theories say that long-term income is the primary determinant of consumption and savings and consequently income and consumption have a long term relationship. These two theories are very important in studying the consumption and savings behaviour of households because they break rank with the simple Keynesian function by saying that consumers do not concentrate exclusively on their current disposable income but they rather look ahead upon their future earnings. However, expected future disposable income can only be estimated from current and past incomes, so permanent income is a weighted average of current and past income levels. On the other hand, both theories just differ in the sense that while the LCH stands that current income changes systematically as people move through their life cycle, the PIH sustains that current income is subject to random, transitory fluctuations (Mankiw, 2007).

The LCH completed that it is necessary to save money during the early ages to be able to provide for retirement. Modigliani later explained that the LCH is a theory about individual and aggregate wealth meaning that the young population has little wealth, the middle-age individuals will possess more while people at their retirement age will possess very little. Though the LCH is useful in examining household's consumption and savings decision, we should also emphasize that it may not hold perfectly in reality because in real life, households are faced by credit constraints (Philbrick & Gustafsson, 2010). Financial deregulation is a cause of these credit constraints. Nevertheless, Deaton (2005) maintained that the LCH is old-fashioned. The author declares that prior to earlier works; it was discovered that the elderly do not dispose of their assets in the way that the theory requires. Therefore, the LCH has been subject to some criticisms. In lieu of this, according to Deaton (2005), Modigliani did not take into account the uncertainty about the death of the people. Doubting about the date of their death, the middle age people may limit the degree at which they save their money for retirement. Consequently, it might cause involuntary bequests (property belonging to someone who they say that, after their death, they wish to be given to other people). Deaton (2005) also noted that the most frequent challenges faced by the LCH is whether real life data really supports the fact that people save when they are young and run down their assets when they are old. As a result, because we live in a world faced by uncertainty, it becomes a challenge when we consider a LCH model faced by these uncertainties.

Modigliani's main idea about the LCH is that young individuals will save early so that when they are old, they will have money to spend. But at this stage, we ask ourselves if the younger individuals die early and do not reach the retirement age, is the LCH still going to hold? This therefore constitutes a very huge criticism in the sense that Modigliani did not design an edition of the LCH in which families are believed to exist for ever. We therefore discerned that though the LCH has been subject to criticism, it however serves as a basis for the theoretical background when it comes to explaining why households save and enter into debt.

Through the investigation and analysis of the two theories forming the base of our dissertation in the choice of our variables, we can now conclude which variables to include in our model. Also, we are able to discern which expected signs our variables will take at the end of our econometric investigation.

In summary, based on the theoretical frameworks, the possible expected signs of the variables affecting household debt are shown in Table 2.1.

Table 2.1: Possible Expected Signs of the Variables

Variables	Possible signs
House price index	+
Inflation (CPI)	-
Income	-
Prime rate	-
GDP	+
Household expenditure	+
Household Savings	-
Unemployment	-

Based on the expected relationship provided by the theories, we tested whether these hypotheses hold in the context of South Africa. Having discussed the existing theories explaining household debt and saving behaviour, it will be of interest to our study to briefly discuss the possible measures of household debt. In the following section, we discuss the different measures used to evaluate household debt in different countries.

2.3 MEASUREMENT OF HOUSEHOLD DEBT

Generally, several measures exist to access a country's household debt situation. The three mostly used measures are the household debt to disposable income, the interest payment to disposable income and the household debt to asset ratio.

2.3.1 Household Debt to Disposable Income Ratio

This ratio actually measures the household gross debt as a proportion of the disposable revenue of households. This ratio is very important in financial institutions because it enables them to associate a household's debt payments to the salary he/she generates. It therefore allows the creditors to know how likely the debtor is going to refund the loan. Hence, this implies that if the percentage is too high, households will find it very difficult to settle their debt and acquire other loans.

This ratio is generally calculated by dividing the gross household debt by the household disposable income.

2.3.2 The Debt Service Ratio

Also called the interest payment to disposable income, the debt service ratio is a measure used by financial moneylenders to access whether a household has already too many liabilities. It actually enables banks to see how much of the household's income is already being consumed on other related payments and therefore produces a measure of the household's competence to cover its debt. However, when using this ratio as a measure of the household debt in a country, it is important to emphasize that changes in interest rates may have important effects on this ratio.

2.3.3 The Debt to Asset Ratio

Otherwise known as the gearing or the leverage ratio, the debt to asset ratio is a measure which shows the percentage of a household's assets which are financed through debt. It is calculated by dividing the aggregate total liabilities of a household by the aggregate total household assets. In this regard, households with very high debt to asset ratios are designated to be "extremely leveraged" and might face serious difficulties if their lenders ask them to repay the advances. Yet, this ratio might be affected if house prices in the mortgage market are subject to changes.

However, in the context of South Africa, the only measure used to identify the household debt in the economy is the household debt to disposable income ratio which is supplied by the South African Reserve Bank.

2.4 CONSEQUENCES OF INCREASING HOUSEHOLD DEBT

Increasing household indebtedness can have huge macroeconomic repercussions in the economy because households are exposed to several shocks in the economy. These shocks mostly include shocks to changes in assets prices, shocks to changes in interest rates and shocks to income.

We note that high debt levels may cause economic recession like the one experienced in the financial crisis 2007/2008 (IMF, Apr 2012). It was acknowledged that the financial crisis of 2007/2008 was mainly caused by the US housing bubble. Housing constitutes the most important asset of the household balance sheet and also constitutes one of the most important reasons why households enter into debt. So, increased debt may expose households to the shocks in changes in house prices. Therefore, a fall in house prices will cause a decrease in household's wealth thereby causing consumption to fall. With the recent financial meltdown, we realized that it was mainly driven by the increasing debt with households not being able to pay back their mortgage (IMF, Apr 2012).

With mounting household debt, households are also very sensitive to the changes in interest rate. Debelle (2004) declared that households are even more sensitive to changes in interest rates than a rise in unemployment. However, it was noted in the literature that households may encounter this effect depending whether they have a fixed or variable mortgage rate. Countries practicing a variable mortgage rate will experience a greater repercussion than countries having a fixed mortgage rate. For example in South Africa, the maximum period commercial banks offer fixed mortgage rates is 24 months⁴(<http://www.privateproperty.co.za/news/property-market-news/fixed-and-variable-mortgage-rates.htm?id=25>) because it entails higher risks on the side of the banks who is considered to be the lender. It involves higher risks because when commercial banks lend

⁴Based on an article written by Jacques du Toit, a Senior Property Economist of the ABSA Group, He confirmed that South African commercial banks offer clients fixed mortgage rates for periods of 12, 18 or 24 months. Of which we therefore confirm the maximum period to be 24 months.

money on a fixed rate to households, the cost of servicing the debt remains fixed over that particular period of time. On the other hand, if the households fail to repay back their debt, the interest rate will still remain the same and the banks will lose. To overcome this scenario, the maximum period they can offer fixed mortgage rates is 24 months.

Concerning income shock, unemployment is the biggest shock households can face. A rise in unemployment implies that households will possess lower income and as such they face difficulties in repaying their debt. Lower income entails that households will be faced by a reduction in their current spending and consumption. Consequently, a shock to income will end up having significant effects on household expenditures.

2.5 COMPOSITION OF HOUSEHOLD DEBT IN SOUTH AFRICA

To fully understand the indebtedness of households in South Africa, we give a brief discussion of the composition of South African household debt which includes mortgage debt and consumer credit. In essence, we expound the fact that the debt under study in this dissertation is the overall (gross) household debt.

2.5.1 Mortgage Debt

Households most often enter into loans to buy homes and other permanent assets (cars, etc.) and in turn offer these assets as security for the loan. This type of loan is called mortgage debt. This loan is granted to consumers on the basis of their annual income and the value of the insured assets. Regularly, this type of debt has monthly payments that are due at the beginning of every month. Interest rate for this type of loan is fickle. Since the interest rate is flexible, the amount of money paid back each month varies in accordance with the interest rate flexibility (Van der Walt & Prinsloo, 1995). One advantage of this type of loan is that repayment can take up to 30 years but the longer the term, the more interest you will pay.

2.5.2 Consumer Credit

Also called consumer debt, Consumer credit is a debt somebody incurs for the purpose of purchasing a good or a service. This component of household debt includes open accounts, personal loans at banks, credit cards, installment sales and lease agreements.

2.5.2.1 Open Accounts

This includes unsettled balance by households to dealers. The main aim of this account is to buy goods and services from traders. Buying on this type of accounts allow the consumers to separate the time of payment of the goods and services from the moment he/she actually comes into possession of these goods and services. The period of credit extension is usually short and unsettled debts are paid within one calendar month of the date of the transaction.

2.5.2.2 Personal Loans at Banks

This type of loans falls among the unsecured loans. Unsecured loans are loans granted directly to consumers based mostly on their financial position, credit history, credit worthiness and general reputation. Personal loans are very risky for the lender because he relies only on the signature and the borrower's promise to pay it back. Therefore, the loan is not secured by any guarantee. Regularly, the interest rate for this loan tends to be very high. Therefore, only customers who possess an account in the bank will be able to benefit of overdraft facilities where they can withdraw money above the maximum amount deposited. Nevertheless, loans can also be granted to individuals who do not possess an account in the lending institution. With the characteristic of being an unsecure loan, the lender of such institutions might entail a co-signer or guarantor.

2.5.2.3 Credit Cards

This type of debt falls under the consumer debt and is also considered as an unsecured debt. This type of debt is actually accessed through credit cards. Credit card facilities provide the consumers with a cooler method for the purchase of goods and services. Credit card debt accumulates when the client does not pay the money that he/she has spent.

2.5.2.4 Instalment Sales and Lease Agreements

Installment sales agreement is an agreement between a consumer and a supplier regarding the purchase of a property. This kind of accord has a very good advantage of creating a direct relationship between the buyer and the lending institution. However, inconveniency may arise where the owner does not automatically become the full owner of the property though he possesses the good. The property might be taken back by the seller if he misses a payment. Therefore, towards evading such circumstances, the buyer may also decide to pay cash.

On the other hand, lease agreements are arrangements where the goods are hired to the buyer but there is no agreement that he will become the owner even after the expiry of the lease agreement (Prinsloo, 2002).

2.6 REVIEW OF THE EMPIRICAL LITERATURE

The aim of our study is to examine the indebtedness of households and what measures have been and still need to be done to encourage consumers to alleviate household debt. Previously, we discussed the theoretical background explaining the indebtedness of households. Here, we mainly survey the existing literature seeking to address the determinants of household debt in South Africa and other countries. Related studies that examined the impact of shocks are also considered. This literature review encapsulates the relevant literature about the study of household indebtedness in South Africa as well as in other countries.

Studying the financial situation of households necessitate us to take a general look at the savings behavior of households. Literature on household savings and debt has been done since 1999 through the work of Aron, Muellbauer and Prinsloo. According to Prinsloo (2002), personal savings expressed as a percentage of disposable income declined over the past 20 years. He also confirmed that the household sector's indebtedness rose at a rate that more or less corresponded with the rate of increase in the disposable income. We agree with that because according to the South African Reserve Bank (SARB, 2009), 13.65 million households in South Africa had at their disposal a combined income of R1, 631 billion. This represents a nominal growth of 6.5% in comparison with 2008, when the household income was 1,531 billion. The studies of the above-mentioned authors were based essentially on estimating the composition of household balance sheet, the determinants of savings and the impact of financial liberalization in South Africa. But none of these studies have critically examined the indebtedness of households and this is of great importance to us. It is however, important to mention that the main concepts involved here are first of all household debt followed by savings. Savings, because we believe that if households do not save, they will be forced to go into debt to satisfy their consumption.

South African households are essentially known for their inability to save. According to Prinsloo (2002), savings by the household sector is defined as that part of current income,

after the payment of direct taxes which is not consumed or transferred as part of household current expenditure. Dissaving occurs when current expenditure exceeds current income. Household savings as a percentage of GDP stood only at 2 % in the last quarter of 2005 (SARB, 2005). In 2002, Prinsloo indicated that an inverse relationship was detected in the early 1980's between the ratios of household debt to personal disposable income of households. The saving ratio of households deteriorated in the 1980's and this coincided with the greater use of credit by households. The author also highlighted that there was an increase in the net wealth of households relative to their personal disposable income. However, this ratio of household debt to disposable income continues to increase. Before the GFC, that is between 2004 and mid-2007, household debt rose rapidly and this was mainly motivated by the briskly rising prices of houses. This increase in household debt was also driven by the relatively low interest rate and easier access to credit by households.

Several studies postulated that household debt and savings are somehow related. According to Kotzé and Smit (2008), the high level of household debt in South Africa is due to a lack of a comprehensive saving culture among South Africans. This is caused by financial illiteracy on the part of the consumers as they spend almost all of their income on consumption leaving little money for savings and investments (Lorgat, 2003). Our study's approach is the same in that while studying the financial situation of households, we take a closer look at their saving behaviour because these two variables were proven to have a close relationship. Consequently, we will be able to identify the connection between household debt and savings by means of a detail econometric analysis.

Studies which examined the impact of the 2008-2009 financial crisis on the determinants of household debt in South Africa are limited. Household indebtedness has been subject to research in many different countries. Among them, we mention Philbrick and Gustafsson (2010) who explored the determinants of the household debt to disposable income ratio in Australia using both the long-run cointegration analysis and a short run error correction model. The authors considered the theoretical view of the LCH proposed by Ando and Modigliani which supports that a household can maximise utility over its life-time subject to an inter-temporal budget constraint. The results of the long-run cointegration analysis showed that the change in the debt ratio depends positively on house prices and negatively on interest rates. On the other hand, the error correction model (ECM) affirmed that in the short-run, the change in the debt ratio depends positively on the change in house prices and the consumer

sentiment index, and negatively on inflation and the error term. Nevertheless, we noticed that the authors used a slightly different approach in the estimation of their long-run equation. They performed the Johansen Cointegration analysis and found that there exists only one unique cointegrating vector. They proceeded with the Fully Modified Ordinary Least Squares (FM-OLS) developed by Phillips and Hansen (1990). Based on Phillips and Hansen (1990), the authors emphasized that the FM-OLS is used when only one cointegrating vector is found in the Johansen analysis and it provides efficient estimates of the long-run relationship between variables. In their results, they indicated that the gain they had from using FM-OLS over the single OLS is not very significant, and instead they recommended that an unrestricted ECM estimator should be used, in which the short-run and long-run is estimated simultaneously.

In accordance with these authors, our study employs the theoretical framework of the LCH and the PIH as a base for the choice of our variables and for the construction of our model. Also, our study solely relies on the simultaneous estimation of the long- and short- run relationship using the VECM. Similarly, we will adopt the long-run cointegration analysis and the short-run ECM to analyse the significant long and short-run relationship between household debt and house prices, inflation, income, prime rate, GDP and household expenditures. The approach of the cointegration and short-run ECM analysis has also been chosen because it has been widely recognized to model macroeconomic and financial time series data (Hendry & Juselius, 2000).

Heever (2007) used the ordinary least squares (OLS) analysis to attempt an estimation of the sensitivity of insolvencies and household debt to changes in interest rates and house price inflation. The determinants of household debt to disposable income was also done through an econometric study by Aron and Muellbauer (2000 a,b). The authors utilized interest rates, house prices, financial liberalization, pension and liquid assets components of wealth as the key determinants of household debt. Contrary to these authors, we will use the cointegration analysis in our study to attempt building a household debt model for South Africa. The OLS method has not been used a lot in the literature to perform econometric analyses to find out the main influences of household debt in South Africa in addition to in other countries. This method has been exposed to various criticisms in the literature. The OLS method appears only to be significant when we are dealing with stationary variables and is not able to provide us with detailed results about the short-and long-run relationships between the variables.

Therefore, because our study is dealing with variables that are non-stationary and we essentially want to discover the short-and long-run relationship that exists between our variables, we will use the VECM analysis.

Meng *et al.* (2011) explored the possible causes of Australian household debt using a Cointegrated Vector Autoregression (CVAR) model. The study employs seven variables to analyse the main reasons why Australian households record high debt levels. They used GDP, number of new dwellings approvals (NDWELL), House price index (HPI), interest rate, unemployment, CPI and population. The results sustains that the most substantial cause of increasing debt levels was eventually trailed by house prices and the number of new dwellings. This research found that interest rate, unemployment and CPI contribute to a negative influence in explaining Australia's high household debt levels whereas GDP, HPI, NDWELL and population contributes positively. Likewise, our dissertation employs a similar technique to the CVAR approach referred to as the Vector Error Correction Model (VECM); they appear to be two closely related types of models (Juselius, 2007; Zaytsev, 2010). In addition, we will use the same variables as this study used except for NDWELL and population. The reason why we omit these variables is because the South African economy does not publish quarterly statistics on these variables. South Africa does not actually publish statistics on the number of new dwellings approvals, for that reason we use the House Price Index (HPI) as a proxy for house prices. Besides, their estimation results reject the hypothesis that demographic characteristics play a significant role in rising household debt. In this regard, because we do not have quarterly information about the population in this country, we decided to exempt this variable from our analysis. However, including unemployment as a variable will be significant and could cover the limitation of not having availability of demographic variables in our dissertation. In this regard, it was confirmed by several researchers that unemployment played an important role in explaining the variation in consumer credit.

Supported by economic theory and surveyed in the literature, unemployment represents one of the most significant determinants of household borrowing. Debelle (2004) affirmed that one of the most significant negative shocks to household income is unemployment. The author confirms that a greater proportion of households go in for more debt because they are unemployed. Nieto (2007) studied the determinants of household credit in Spain and developed a model credit for Spanish households and unemployment appeared to be a

significant determinant. Through an econometric investigation, the author confirms that household credit is greatly influenced in the short-run and the long-run by unemployment. The analysis substantiated that households tend to borrow more when they are unemployed. The significance of including unemployment as one of the variables is evident from the abovementioned studies. But due to the unavailability of quarterly data on unemployment in South Africa under our period of analysis, we are therefore unable to analyse its effects in the main data set. We recognize this constraint. Nevertheless, with the accessibility of annual data, we will employ a separate investigation to discover if household debt and unemployment move together both in the long and in the short run. Specifically, the Engle-Granger methodology will help us discover the relationship between household debt and unemployment in South Africa.

All the same, Keese (2012) instead analysed household indebtedness from a psychological point of view. He pointed out that many contributions concentrate mostly on the financial aspects and neglect further influencing factors (demographic and economic characteristics, life satisfaction, health status, etc.). Specifically, the author used the German Socio-Economic Panel data to investigate the main causes of high debt loads. The econometric analysis conducted in this paper supports the important role unemployment plays for the high debt burden tracked by the existing financial state of households (potentials of future revenue). Similarly to this study, our dissertation recognizes the significance of including some demographic variables like the number of children in a household, geographical situation of households, age structure of the population, etc. but unfortunately South Africa lacks quarterly data on such characteristics. However, as previously mentioned, due to a lack of quarterly data, a separate analysis using annual data will be done to examine to what extent unemployment affects the level of household debt in this country. This will consequently increase the relevance of our study.

Notwithstanding, Meng *et al.* (2011) showed the considerable role played by the housing market in explaining the rapid growth of Australian household debt. Seeing that the 2008-2009 financial crisis was mainly caused by the boom of the housing market in the US and exacerbated by the high household debt levels. In this context, we will attempt to discover the relationship that exists between household debt and house prices in South Africa and to determine to what extent the financial crises of 2008/2009 affected these variables.

We consider the body of literature which investigates the impact of shocks on related variables using the GIRF. Among them, Girardi and Paesani (2005) conducted an empirical investigation of the transfer problem for the Euro zone vis-à-vis the rest of the world. They made use of the CVAR (VECM) approach and employed the GIRF to study the convergence speed towards a country's equilibrium position. The authors mentioned that GIRF analysis does not allow giving a structural interpretation to the impulses, but overcomes the model identification problem by providing a significant characterization of dynamic responses to typically observable shocks. In the same way to this approach, Hurley (2010) employed a generalized impulse response investigation to study the relationship between East Asian holdings of U.S. securities and the U.S. short term and long term interest rates. He also used the VECM approach to examine the dynamics and linkages in the variables. Hurley employed the GIRF analysis to trace the response path of the time series to a shock to itself and other variables in the model. This analysis concluded that the low long-term rates in the U.S. may be explained in part by increased Asian holdings of the U.S.

Consistent with these studies, we trace the time paths of the effect of a typical shock in one variable on our remaining variables via GIRFs. Because the IRF is sensitive to the ordering of the variables and may produce misleading results, we therefore employ the GIRF proposed by Perason and Shin (1998) for the simple reason that the responses are invariant to the VAR ordering. Evidently, this method has been used by several other researchers to overcome the difficulties faced by the IRF with the ordering of the variables and this will provide our chapter with more robust results.

Kim (2011) investigated the relationship between household debt and aggregate income in the US using a growth Vector Autoregression Analysis (VAR). This study captures the transitory feedback among the growth rate of debt, GDP and net worth and observed that there exists a positive feedback process in the short-run between debt and aggregate income. The author also utilizes the VECM to find if there exist a significant connection between household debt and output. He designed a model by including investment and corporate debt and the empirical results indicated that investment is still the dominant of macro fluctuation related to household debt. The results of the VECM also concluded that there exist a significant negative relationship between household debt and output (GDP). One interesting feature of this paper is the use of the GIRF to study the impact of various shocks on the consumer debt. The author found that a shock to consumer debt is accompanied by an

increase in consumption and Gross Domestic product (GDP) and similarly observed that investment as well as corporate debt permanently increases in response to a shock to consumer debt. However, it was concluded that the results of the GIRF were sensitive to model selection. By model selection, we mean here the selection of the different lag lengths. VAR analyses are usually more appropriate when dealing with data which are stationary at their levels. In our study, we are mostly dealing with macroeconomic variables and these variables are essentially known to be non-stationary. Consequently, likewise this author we apply the VECM approach to investigate the main determinants of household debt in South Africa. Still in accordance with the author, we employ the same method of the GIRF to investigate whether the GFC shock has a negative impact on household indebtedness in South Africa.

Mukuddem-Petersen *et al.* (2010) employed the VAR model and GIRF to study speculative funding and its impact on subprime mortgage product pricing. They employed the GIRF to overcome the weakness related to the ordering of the variables and to ensure more robust results. They concluded that mortgage price is mostly affected by shocks from mortgage rates. Similarly, our chapter utilizes the GIRF approach to inspect the impact of shocks to household debt in South Africa. Also, the GIRF was used to bypass the limitations faced by the Impulse Response Function (IRF).

Table 2.2 presents the strengths and weaknesses of the different methodologies discussed so far:

Table 2.2: Comparison of Methodologies

METHODOLOGY	STRENGTHS	WEAKNESSES
Engle-Granger	1. It tests for the existence of a long and short-run relationship between two non-stationary processes. 2. It may also be used in a multivariate context.	1. The results are more robust when dealing with only two variables. 2. It cannot pick up more than one cointegrating vector (or more than one relationship). 3. It does not allow the construction of IRF_s.
VAR	1. Treats all the variables as endogenous in the system and does not impose a priori restriction. 2. It is a powerful to examine the properties of the data. 3. It avoids incredible identification restrictions. 4. Allows the researcher to generate forecasts for the variables. We can therefore obtain IRF_s of selected shocks and interpret the identification of permanent and transitory shocks.	1. It requires longer time series. 2. Does not provide a detailed analysis of long and short-run relationship between variables. 3. Do not identify structural coefficients nor do they take seriously the relevance of unit root test. 4. Too many lags included in the model do not make it easy to interpret the results 5. The results are sensitive to model specification. 6. The estimated parameters of the model cannot be given a meaningful economic interpretation
VECM	1. Very informative about the data and allows the analysis of non-stationary data. 2. It allows the examination of several cointegrating relationships. 3. It distinguishes between the longer and shorter term dynamic effects. 4. We can obtain IRF_s to selected shocks.	1. Needs long time series 2. Robustness of results especially with short samples. 3. Results are sensitive with model specification (variables included, sample size, and choice of lag length).

With the different advantages and drawbacks of the methodologies discussed above, we essentially decided to choose the VECM method. As earlier discussed, this method is mainly chosen to capture the short-run and long-run dynamics that the VAR cannot afford. Also, the VECM yields more efficient coefficients estimates as compared to the Engle-Granger methodology. This is because the VECM is a full information maximum likelihood estimation model, which allows for testing for cointegration in a whole system of equations (Maysami & Koh, 2000). In addition, Maysami and Koh (2000) mentioned that the VECM appears better because it avoids carrying over the errors from the first step into the second, as is the case with the Engle-Granger methodology. Although it suffers some difficulties, the VECM has been used by many other researchers in the recent years. However, it has been roughly mentioned in several papers that the VECM results will be more robust with the availability of a large number of observations. Actually, none of these studies actually specified the exact or the minimum number of observations needed to perform a VECM.

Table 2.3 presents some literature used in this study as well as other related studies using the VECM with special attention with the number of observations they used.



Table 2.3: Analysis of Selected Literature to Compare the Number of Observations

LITERATURE	TOPIC	METHOD	NUMBER OF OBSERVATIONS
Maysani & Koh, 2000	A VECM of the Singapore Stock Market	VECM	85
Chawluk, 2000	Estimates of demand for money and consumption functions for the household sector in Poland , 1967-1999	VECM	33
Anderson, Hoffman & Rasche, 2002	A Vector Error Correction forecasting Model of the US economy	VECM	176
Martinez-Carrascal & Rio, 2004	Household borrowing and consumption in Spain: a VECM approach	VECM	80
Sreedharan, 2004	A VECM of Stock Market Returns	VECM	2780
Babatunde & Adebafi, 2005	Long Run Relationship between Education and Economic growth in Nigeria: Evidence from the Johansen Cointegration Approach	VECM	34
Farzanegan & Markwarat, 2007	Effects of oil price shocks on the Iranian economy	VAR	68
Oikarinen, 2009	Household borrowing and metropolitan house-price dynamics- Empirical evidence from Helsinki	VECM	126
Oikarinen, 2009	Interaction between house prices and household borrowing: the Finnish case	VECM	128
Omisakin, Adeniyi & Omojolaibi, 2009	A VECM of Energy Price Volatility of an Oil Dependent Economy	VECM	36
Anaraki, 2009	The European stock market impulse to the US financial crisis:	VECM	124
Caporale & Soliman, 2010	Stock Prices and Monetary Policy: An Impulse Response Analysis	VECM	67
Gimeno & Martinez-Carrascal, 2010	The relationship between house prices and house purchase loans: the Spanish case	VECM	101
Martins, 2010	Fiscal Dynamics in Ethiopia, a CVAR model with quarterly data	CVAR	64
Philbrick & Gustafsson, 2010	Australian Household Debt: an empirical investigation into the determinants of the rise in the debt-to-income ratio	VECM	117
Chu, 2011	Relationship between macroeconomic variables and net asset values (NAV) of equity funds: Cointegration evidence and vector error correction model of the Hong Kong Mandatory Provident Funds (MPFs)	VECM	109
Ni, Huang, & Wen, 2011	Interest rate, Unemployment rate & House market in the US	VECM	202
Meng, Hoang & Siriwardana, 2011	The determinants of Australian household debt: A macro-level study	CVAR	72
Patterson, 2011	Essays in macroeconomics: A VECM of household debt and the macro-economy	VECM	92
Oriavwotol & Eriemo, 2012	Oil Prices and the Real Exchange Rate in Nigeria	VECM	31

From Table 2.3, we noticed that the number of observations used in the different studies vary and none of them actually specifies how many observations is needed to construct a significant VECM. However, when putting aside the study done by Sreedharan (2004) which used 2780 observations (because we considered it exorbitant), we noticed that the average of the rest of the studies tallied to 93 observations. Therefore, to ensure that our results are accurate and robust, we will utilize a minimum of 105 observations which is slightly above the average of 93 observations calculated. By doing this, we are sure to be working in the range of observations used by previous studies and thus, we are sure to produce efficient and reliable results.

Clearly, the impact of this crisis on household indebtedness is an unexplored research field in South Africa. Various studies on the relationship between household debt and other macroeconomic variables have been examined in different countries. Our study is significant because to our knowledge, it will be the first study in the South African context to investigate the determinants of debt-to-income using a VECM analysis and more especially to analyse the impact of the financial crisis using the GIRF.

Literature on household savings and debt, as well other related studies that examined the impact of shocks has been surveyed in this chapter. We provided an explanation on the components of household debt, how household debt can be measured, the different components of household debt and a theoretical review were also examined. However, one of the shortcomings of the literature on household savings is that it fails to provide detailed information on the indebtedness of households in South Africa which is of interest to our study. Surveying the literature, we observed that few studies have examined the determinants of household debt in South Africa and none of them have studied the impact of the 2008-2009 financial crisis on the indebtedness of households. In this regard, our econometric analysis exploring the main reasons why households record very high debt levels will be novel and will greatly contribute to the literature. Some empirical studies have been able to investigate the main reasons why households enter into debt; it will then be of special interest to this study to overcome the failures of other papers by accessing the impact of the 2008-2009 financial crisis on household indebtedness in this country using the GIRF.

CHAPTER 3

DATA AND METHODOLOGY

“Statisticians, like artists, have the bad habit of falling in love with their models”

George Box

3.1. INTRODUCTION

3.2. MODEL SPECIFICATION

3.3. DATA DESCRIPTION

3.4. MODELLING STRATEGY

3.1 INTRODUCTION

This chapter presents and specifies the econometric model; it describes, defines and justifies the data selection. Specifically, we introduce the estimation technique employed in the study and all the tests that were performed to examine the properties of the variables. In particular, the study uses the time series data to estimate the correlation among the variables. In so doing, we will be able to establish the cause and effect interactions between these variables. Also, we will investigate how the variables being studied respond to given exogenous shocks. The estimation techniques used will mainly be quantitative in nature as stated in Chapter 3. We are persuaded to estimate our different system of equations through the VECM framework because it allows for contemporaneous and lagged interconnection between the variables, thus providing more robust results (Zaytsev, 2010).

3.2 MODEL SPECIFICATION

This section incorporates a brief discussion about the variables used to build our model. As concluded in the previous chapter, the theoretical and empirical literature suggests the

inclusion of a possible number of variables in our econometric investigation that may be influencing household debt.

We include the real house price index in the model because it falls among the most important assets of households. Also, the LCH justifies that households go in for more debt when the price of houses increase. Consumer price index is included in the model as a proxy to measure inflation. Its main aim is to capture the speed at which household debt erodes. Also, it investigates if households are influenced to go in for debt when the prices of goods and services fluctuate. Additionally, we include real income in the model to identify if the increase in the debt to income ratio is due to the lack of money in the households. In addition, real prime rate is included in the model to capture how the change in interest rate affects household's decisions to borrow. Similarly, we involved real gross domestic product in our analysis to measure how the increase in the economic growth of the country could possibly affect household debt. The theory confirms the fact that the more households spend, the more their income will decrease and the more they will opt for more debt. As a result, real household consumption expenditure is included to capture this relationship. Finally, real household savings is incorporated into the model to investigate if the increase in household debt is due to a lack of saving behaviour among households.

We therefore conclude that including all these variables in the model, the household debt function for South Africa can be specified as follows:

$$\text{LRHD} = f(\text{LRHPI}, \text{LCPI}, \text{LRIN}, \text{LRPR}, \text{LRGDP}, \text{LRCON}, \text{LRS AV})$$

The regression equation of household debt will therefore be of the form:

$$\begin{aligned} \text{LRHD}_i = \beta_0 &+ \overbrace{\beta_1 \text{LRHPI}_i}^{+} + \overbrace{\beta_2 \text{LCPI}_i}^{-} + \overbrace{\beta_3 \text{LRIN}_i}^{-} \\ &+ \overbrace{\beta_4 \text{LRPR}_i}^{-} + \overbrace{\beta_5 \text{LRGDP}_i}^{+} + \overbrace{\beta_6 \text{LRCON}_i}^{+} + \overbrace{\beta_7 \text{LRS AV}_i}^{-} + \mu_i \end{aligned}$$

Dependent variable

LRHD= Natural log of real household debt

Explanatory variables

LRHPI=	Natural log of real house price index
LCPI=	Natural log of consumer price index
LRIN=	Natural log of real income
LRPR=	Natural log of real prime rate
LRGDP=	Natural log of real gross domestic product
LRCON=	Natural log of real household consumption
LRSV=	Natural log of real household savings
β_0 =	Intercept
β 's=	slope of coefficients
μ =	Error term

3.3 DATA DESCRIPTION

The level of household indebtedness in South Africa is influenced by many factors. As formerly stated, we use LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON and LRSV to analyse the determinants of increasing household debt. In this dissertation, we employ quarterly data (1985Q1 – 2012 Q1) because it offers several advantages over studies that employ annual variables and also allows intra-year dynamics. The list of the data used in our model and their respective sources is described in Table 3.1 beneath.

Table 3.1: Summary of Data Description

VARIABLE	MEASURE	SOURCE
1. Real household debt to disposable income	Quarterly data measured in millions	SARB
2. Real House Price Index	Quarterly data (index base year 2008=100)	ABSA bank
3. Inflation	Quarterly data (index base year 2008=100)	Statistics South Africa (Stats.sa)
4. Real income	Quarterly data measured in millions	SARB
5. Real Prime rate	Quarterly data measured in percentage	SARB
6. Real GDP at market price	Quarterly data measured in millions.	SARB
7. Real household consumption expenditures (Total PCE ⁵)	Quarterly data measured in millions	SARB
8. Real household savings	Quarterly data measured in millions	SARB
9. Unemployment rate	Annual data	Index mundi ⁶ sourced from IMF

SARB data tables are available at <http://www.sarb.co.za>

ABSA bank data is available at <http://www.absa.co.za>

Stats.sa data is available at <http://www.statssa.gov.za>

Index mundi data is available at <http://www.indexmundi.com>

Below, we discuss the different alterations that were made to the data.

1. Real household debt to disposable income

The debt to income ratio is included in the model to capture the debt owed by the household sector. The nominal household debt and nominal household income were separately deflated with CPI to obtain a ratio of real household debt to disposable income.

⁵Total PCE is refer to as total personal consumption expenditures of the household sector.

⁶Index mundi is a secondary source of data statistics which source its information from the IMF

2. Real house price index (RHPI)

The nominal monthly data measured with an index of 2000 as a base year collected from ABSA bank is utilized and averaged to get our data. The data is transformed into a new base year 2008=100. The nominal data is then transformed into by deflating it with the CPI⁷.

3. Inflation (CPI)

We include CPI data from all urban areas extracted from Stats.sa measured with an index of 2008=100 as the base year.

4. Real income

The nominal income taken from the SARB was deflated with the CPI.

5. Real Prime rate

This data is provided only on a nominal monthly basis by the SARB. So we averaged the data on a quarterly basis to meet our desired frequency and later on converted it to real data by deflating it with the CPI.

6. Real GDP at market price

Nominal GDP extracted from the SARB was converted into real GDP by deflating it with the CPI. Instead of the GDP deflator, we use the CPI as a deflator to get real values and it represents the true amount of goods and services purchased by households at the corresponding price.

7. Real household consumption expenditures

Nominal household consumption expenditures extracted from the SARB was converted into real values by deflating it with the CPI.

8. Real household savings

Nominal household consumption expenditures extracted from the SARB was converted into real values by deflating it with the CPI.

⁷The data obtained from ABSA bank was nominal and monthly. We took the mean of 3 months to get the quarterly data since 1 quarter = 3 months. Again, the variable is transformed into 2008 as a base year to get uniformity with the other variables. Lastly, the variables were transformed into real variables by deflating it with inflation. This is done by dividing the nominal value by the CPI value and we multiply by 100.

9. Unemployment

The unemployment data is obtained from the Index Mundi website. Index Mundi is a secondary site which sourced its information (statistics) from the International Monetary Fund. This data will be used apart from the main data set to investigate if it is closely related to household debt.

3.4 MODELLING STRATEGY

Since most macroeconomic variables are known for their non-stationarity characteristics, the method employed in this dissertation is the VECM approach also called the CVAR. Basically, the purpose of using this approach is to find out the main influences of the increase in household debt in South Africa. We applied this technique because it has been used previously in a number of studies and is established as the appropriate method to employ especially when we are dealing with multivariate time series data. Other methods like the Ordinary Least squares (OLS) could have been employed in this study but the difficulty is that they do not offer the same advantages as the VECM. The problem with the OLS regression is that it can only produce efficient results if the time series variables under study are non-stationary. As a result, performing a regression using the OLS in this study will evidently offer us wasteful results because we are dealing with macroeconomic variables which are mostly known for their non-stationarity. The use of non-stationary data can lead to spurious regressions unless they are cointegrated. If two variables are trending over time, a regression of one on the other could have a high R^2 even if the two are totally unrelated. If the variables in the regression model are not stationary, then it can be proved that the standard assumptions for asymptotic analysis will not be valid. In other words, the usual “ t -ratios” will not follow a t -distribution, so we cannot validly undertake hypothesis tests about the regression parameters (Al-Ezzee, 2011). So, rather than using the OLS, it is advisable for us to use the VECM because, we will be able to model the non-stationary properties of our time series.

This dissertation uses the VECM which consists of the Johansen cointegration technique and the short run error correction approach. In the empirical analysis, we test for the existence of a long-run relationship among our variables and the utilization of the error correction modelling assist us to capture the short run dynamics of the variables. Information on the long term co-movements among the variables is also helpful for specifying the appropriate model to construct the variance decomposition and impulse response functions.

To achieve the main goals of this dissertation the following VECM steps are systematically implemented. Furthermore, a stepwise summary is illustrated in Figure 3.1.

Step 1

Our first step is to gather the time series data that have been modified into the same frequency and same base year.

Step 2

The variables are transformed into logarithmic forms to reduce the problem of autocorrelation and heteroskedasticity in the course of our study (Ahmed, 2007) and also to have an easier graphical visualization and interpretation of the data.

Step 3

Here, we offer descriptive statistics of the variables to see the nature of the data.

Step 4

We propose a visual inspection of the data to see if the variables are found stationary or not at their level.

Step 5

At this point, we test for unit roots among the variables by applying the Augmented Dickey Fuller test (ADF), the Phillips Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

Step 6

We have to choose the optimal lag length that is best suitable for our model. This will be done using the AIC, SIC and HQ information criterion.

Step 7

Testing if our variables are cointegrated using the Johansen cointegrated test. This involves testing for the number of cointegrating relationships (rank of the matrix) using both the trace and maximum eigenvalue statistics.

Step 8

If the results of the Johansen test supports that the variables are not found to be cointegrated, then we should estimate a VAR. On the contrary, we should proceed with

the VECM if the variables are found to be cointegrated.

Step 9

Subsequently, we will proceed by estimating the complete VECM. The entire VECM will provide us with detailed information about the long run and short run relationships that exist between our variables. Furthermore, we will impose restrictions based on economic theory on alpha and beta coefficients in order to get unique solutions

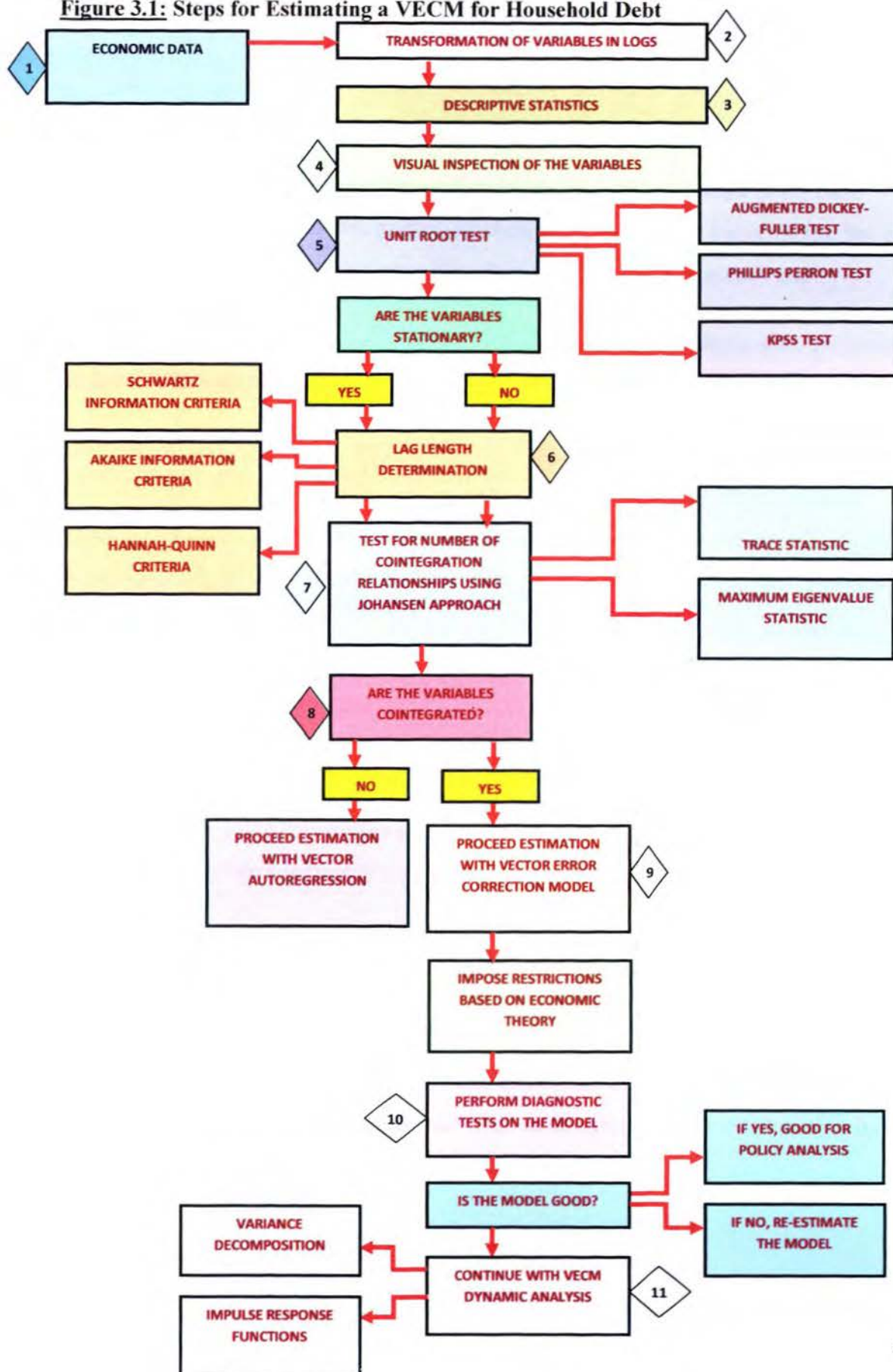
Step 10

Diagnostic tests such as the autocorrelation test, the normality and heteroskedasticity test and the stability test will be performed to check if the estimated model is good. If the model is found good, then it can be used for policy analysis. On the contrary, it will need to be re-estimated.

Step 11

Additionally, we will continue with the dynamic analysis of the VECM results. At this step, we will estimate the variance decomposition and the generalized impulse response function (GIRF). We employ these two tests to analyse the impact of shocks on household debt and other variables considered in this study.

Figure 3.1: Steps for Estimating a VECM for Household Debt



In the sequel, we present a detailed explanation for every step in Figure 3.1.

3.4.1 Gathering of the Variables

As mentioned previously, due to the different frequencies and measurements of the time series variables used in this study, we performed some modifications on the variables. So, our first step will be to gather our variables that have been adjusted for consistency and standardization purposes.

3.4.2 Log Transformation of the Variables

Log transformation of variables is very useful especially in data analysis. The time series variables were transformed into their natural logarithms to provide some uniformity and also to avoid some misspecifications problems later when we conduct our econometric analysis.

3.4.3 Descriptive Statistics

Before we begin with the econometric analysis of the relationship between household debt and its determinants, we will first examine the time series properties of the variables under study. This entails providing descriptive statistics of our variables of interest. The purpose for considering the descriptive statistics is to provide a summary of the data in a quantitative form. It presents information about the mean, median, standard deviation, skewness and kurtosis of the data. According to Mahadeva and Robinson (2004), it is common for most macroeconomic variables to increase or less frequently to decrease over time. The authors asserted that variables tend to depart from any given value as time goes on and they will show a trend if their movement in time is predominantly in one direction. Descriptive statistical analysis was shown to be a good start when conducting any econometric approach.

3.4.4 Visual Inspection and Stationarity

The visual inspection of our variables of interest will be used as preliminary method of analysing our data. By so doing, we will be able to visually examine the fluctuations of the variables over the chosen timeline. We will then conclude from a graphic illustration how the

financial crisis of 2008-2009 affected our variables of interest. Also, this offers us a great advantage in the sense we can initially detect which variables are stationary at their level or at their first difference. We will then be able to predict or confirm the results of the stationarity test that will be conducted later.

A stationary process is one whose statistical properties such as mean, variance, covariance, autocorrelation, etc. are constant over time. Conversely, a non-stationary process has one or more basic properties that do change over time. One problem arising with time series data is that the independent variables can appear to be more significant than they actually are if they have the same trend as the dependent variable (Studenmund, 2011).

Most forecasting models are essentially based on the assumption that the time series data must be stationary. Financial institutes, researchers and businesses often use financial and macroeconomic time series data in economic and financial predictions. But, it is well known that most macroeconomic and financial series are usually non-stationary and cannot be modelled or forecasted. Therefore, the regression performed using non-stationary variables may result in a spurious regression which will indicate a relationship between two variables that do not exist. A spurious regression will usually be characterized by a highly significant level of R^2 values, t-statistic and F-statistic.

Some variables appear to be non-stationary mainly because they increase rapidly over time. In this case, spurious regression can be avoided by the inclusion of a time trend as an explanatory variable in the equation. Regrettably, many economic and financial time series data are non-stationary even after the removal of the time trend. Therefore, to overcome this shortcoming and to get efficient and reliable results, it is vital to ensure that the time series variables are stationary before running any regression.

The following unit root test helped us to examine whether our variables are stationary at their level or after their first difference.

3.4.5 Unit root test

Time series generally exhibit a non-stationary pattern in their levels, unit root testing as a pre-testing device for cointegration were carried out in order to determine the degree of stationarity. Many studies have indeed shown that most macroeconomic times series are non-stationary or rather they are around a deterministic trend. If the regression is performed on non-stationary time series data, the results will explain the relationship among the variables only during the period of time studied. This means it will be very difficult to infer the long run relationship among our variables. Equally, regression on non-stationary time-series will give us biased and inefficient results. As a consequence, it is imperative when analysing economic time-series data to conduct initial tests for non-stationarity before proceeding to the complete estimation of our model.

Based on Wooldridge (2006), the simplest approach to begin testing for a unit root begins with an AR (1) model:

$$X_t = \alpha + \rho X_{t-1} + \varepsilon_{t-1}, t=1,2,3,\dots \quad (3.1)$$

where $X_{(t=0)}$ stands for the observed initial value. Therefore, we can test with this equation that the null hypothesis is that X_t has a unit root:

$$H_0: \rho = 1 \quad (3.2)$$

Versus the alternative hypothesis that X_t do not have a unit root.

$$H_1: \rho < 1 \quad (3.3)$$

There are several unit root tests which are designed to render a verdict as to whether a given time series data appears to imply the presence of a unit root or whether it is stationary. The stationarity test employed in this dissertation was done using the three common and appropriate tests: the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. As stated by Ahmed (2007), before performing the following tests, all the variables will first be transformed into logarithms to reduce the problem of serial correlation and heteroskedasticity in the course of our study. These tests empirically helped to verify the stationarity of all the variables used in this study.

Additionally, these tests identify the order of integration in our variables of interest. Specifically, the number of unit roots in a series is the same as the number of times the concerned variable is to be differenced from its lagged values to attain stationarity. This means that a particular time series (Y_t), that contains a single unit root is nonstationary in the level or original form. When it is then differenced, that is, when $\Delta Y_t = Y_t - Y_{t-1}$ is generated, the resulting series therefore becomes stationary (Rufino, 2008).

3.4.5.1 Augmented Dickey Fuller (ADF) test

The ADF test has been originated through the work of Dickey and Fuller (1979) and Said and Dickey (1984). The original version of the Dickey-Fuller test assumes that the error terms in the regression are uncorrelated. When serial correlation is present, the ADF version of the test proposes to include in the regression several lags of the difference of the series to account for the serial correlation. This analysis is used to test for the order of integration on the variables used in the model in order to decide whether the variables follow a non-stationary trend or whether the time series are stationary. Therefore, we can say that the purpose of a unit root test is to determine whether a time series is consistent with I (1) process with a stochastic trend, or if it is consistent with I (0) process, that is it stationary, with a deterministic trend. If this test confirms that our variables are stationary, then we are sure to get unbiased estimates. The ADF test is an augmented version of the Dickey-Fuller test for a larger and more complicated set of time series models. Zivot and Wang (2003), Rossi (2010) affirmed that the ADF test will be valid if the time series X_t is well characterized by an AR (1). The ADF test essentially is based on the estimation of the following regression

$$\Delta X_t = \alpha + \beta t + \delta X_{t-1} + \sum_{i=1}^n \lambda_i \Delta X_{t-i} + \varepsilon_t \quad (3.4)$$

where β_t is a vector of deterministic terms (constant, trend, etc...) and α is the constant. The p lagged difference terms, ΔX_{t-1} , are used to approximate the ARMA structure of the errors, and the value of p is set so that the error ε_t is serially uncorrelated. The error term is also assumed to be homoskedastic. One benefit of the ADF test is that it permits the inclusion of deterministic components and lengths in the regression. The ADF test raises the problem of choosing the number of lags to be included in the test. This is done by a variety of tests. In practical terms, we would like to add enough terms so that the errors are white noise. Tests for optimal lag lengths that are used include the Schwartz Information Criteria (SIC), the Akaike Information Criteria (AIC) and the Hannan-Quinn Criteria (HQC). The optimal lag

length is important to identify the true dynamics of the model. The inclusion of lag lengths in the regression is mostly to get rid of the serial correlation contained in the error terms. Yet, the more lags we include, the more observations we loosing and the sample power of the test generally suffers. Frequently, the lag length is dictated by the frequency of the data besides the sample size. Below are the three cases in which the ADF test is performed:

Case 1: With the constant (or intercept) only

Under this case, the unit root test is based under this regression form

$$\Delta X_t = \alpha + \delta X_{t-1} + \sum_{i=1}^n \lambda_i \Delta X_{t-1} + \varepsilon_t \quad (3.5)$$

This equation includes only a constant to capture the non-zero mean. The hypothesis to be tested is:

$$H_0 : \delta = 0 \quad (3.6)$$

$$H_1 : |\delta| < 0 \quad (3.7)$$

where H_0 is the null hypothesis that X_t has a unit root and H_1 is the alternative hypothesis that X_t does not have a unit root. This formulation is very appropriate for non-trending variables.

Case 2: With a constant (or intercept) and a (deterministic) time trend

Under this case, the unit root test is based under this regression form

$$\Delta X_t = \alpha + \beta t + \delta X_{t-1} + \sum_{i=1}^n \lambda_i \Delta X_{t-1} + \varepsilon_t \quad (3.8)$$

The equation includes a constant and a deterministic time trend to capture the deterministic trend. The hypothesis to be tested remains the same like in the first case.

$$H_0 : \delta = 0 \quad (3.9)$$

$$H_1 : |\delta| < 0 \quad (3.10)$$

where H_0 is the null hypothesis that X_t has a unit root and H_1 is the alternative hypothesis that X_t does not have a unit root. Also, this formulation is appropriate for trending time-series variables. This will frequently be the case for macroeconomic variables.

Case 3: Without a constant (or intercept) and a (deterministic) time trend

The Unit root test will be based under the regression

$$\Delta X_t = \delta X_{t-1} + \sum_{i=1}^n \lambda_i \Delta X_{t-1} + \varepsilon_t \quad (3.11)$$

The equation does not include a constant or a deterministic time trend. The hypothesis to be tested remains the same like in the first two cases.

$$H_0 : \delta = 0 \quad (3.12)$$

$$H_1 : |\delta| < 0 \quad (3.13)$$

This third case is a very special case and is not often use because most regression always include at least a constant.

Decision rule

For all three cases, the t statistic is calculated as follows:

$$t^* = \frac{\hat{\delta}}{\sigma_{\hat{\delta}}} \quad (3.14)$$

Where $\hat{\delta}$ is the estimated coefficient and $\sigma_{\hat{\delta}}$ is the standard error in the coefficient estimate. However, the decision for all three cases is like this:

1. If $|t^*| < |\text{ADF critical value}|$, then we do not reject the null hypothesis. This will then imply that the unit root exists.
2. If $|t^*| > |\text{ADF critical value}|$, then we reject the null hypothesis. This then means that a unit root does not exists.

Hence, whenever we have an integrated time series of order one or greater, we have a non-stationary series. Even though the ADF test is very common in testing for unit root, it was concluded that it has some weaknesses. The ADF test was shown to have low power when average terms are present or when the errors (disturbances) are heterogeneously distributed (http://shodhganga.inflibnet.ac.in/bitstream/10603/3246/12/12_chapter%204.pdf).

3.4.5.2 Phillips-Perron (PP) test

An alternative unit root test, Phillips-Perron (PP) test (Phillips 1987, Phillips and Perron 1988) were conducted to ensure the stationarity of the data series as this test uses non-

parametric correction to deal with any correlation in the error terms. Compared to the ADF test, the PP differs mainly in the way they correct serial correlation and heteroskedasticity in the residuals/errors (Tripathy, 2011). This test uses the Newey-West (1987) autocorrelation and heteroskedasticity consistent variance matrix estimator to correct correlation as heteroskedasticity. Nevertheless, just like the ADF test, the PP test generally offer identical conclusions concerning the interpretation of the test statistics. However, the computation of the PP test statistics appears to be very complex. The PP test estimates the following regression:

$$\Delta Y_t = \theta_0 + \delta Y_{t-1} + \varepsilon_t \quad (3.15)$$

The PP tests the following hypothesis:

$$H_0 : \delta = 0 \quad (3.16)$$

$$H_1 : \delta < 0 \quad (3.17)$$

Under the null hypothesis that $\delta=0$, the PP test statistics are given as follows:

$$Z_t = \sqrt{\frac{\hat{\sigma}^2}{\hat{\lambda}^2}} t_{\hat{\delta}} - \frac{1}{2} \left[\frac{\hat{\lambda}^2 - \hat{\delta}^2}{\hat{\lambda}^2} \right] \left[\frac{n(s.e.(\hat{\delta}))}{\hat{\sigma}^2} \right] \quad (3.18)$$

$$Z_{\delta} = n\hat{\delta} - \frac{1}{2} \frac{n^2(s.e.(\hat{\delta}))}{\hat{\sigma}^2} (\hat{\lambda}^2 - \hat{\sigma}^2) \quad (3.19)$$

From the above equations (3.18 and 3.19), the terms $\hat{\sigma}^2$ and $\hat{\lambda}$ are consistent estimates of the variance parameters

$$\sigma^2 = \lim_{n \rightarrow \infty} n^{-1} \sum_{t=1}^n E(\varepsilon_t^2) \quad (3.20)$$

$$\lambda^2 = \lim_{n \rightarrow \infty} \sum_{t=1}^n E \left(\frac{1}{n} \sum_{t=1}^n \varepsilon_t^2 \right) \quad (3.21)$$

Where the variance of the least square residual is $\frac{1}{n} \sum_{t=1}^n \varepsilon_t^2$, ε_t is a consistent estimate of σ^2 .

The Decision rule of the PP test remains the same as the one discussed above in the case of the ADF test.

Though the PP test tends to be more than the ADF test, both tests have been subject to some criticisms. Both unit root tests are assumed to suffer from severe finite sample power and

sample size. Again, both tests are assumed to have very low power against the alternative hypothesis that the series is stationary. Also, the disadvantage of the PP test is that the results of the test statistics might be very sensitive to model specification. Also, the power of unit root tests diminish as deterministic terms are added to the test regressions (<http://faculty.washington.edu/ezivot/econ584/notes/unitroot.pdf>). That is, tests that include a constant and trend in the test regression have less power than tests that only include a constant in the test regression.

Blanchard (1991) affirmed that when conducting the tests of the unit root hypothesis, the power depends very little on the number of observations (sample size) but it is rather influenced by the period covered by the observations (span). He said that for a given number of observations, the power of the test is largest when the span is longest. He confirmed that for a given data set containing fewer annual data over a long time period will lead to tests having higher power. However, this might not certainly be the case if we use a data set containing more observations over a short time period. The author then terminated that whenever possible; tests of the unit root hypothesis should be performed using annual data over a long time period. Though both tests have been subject to many criticisms, they appear to be the most widely used unit root test.

Nevertheless, because the ADF and PP test are not 100% reliable, we propose another stationary test in this study, The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

3.4.5.3 Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) is an econometric test for stationarity which was proposed by Denis Kwiatkowski, Peter C.B. Phillips, Peter Schmidt and Yongcheol Shin in 1992. This test was developed to test a null hypothesis that a given time series is stationary around a deterministic trend. Actually, this test was intended to complement other unit root tests like the ADF and the PP test (Syczewska, 2010). By testing both the unit root hypothesis and the stationarity hypothesis, the researcher can easily distinguish those series that appear to be stationary, series that appear to have a unit root, and series for which the data (or the tests) are not sufficiently informative to be sure whether they

are stationary or integrated. As cited in Syczewska (2010), Kwiatkowski *et al.*(1992) derived their test by starting with the following model:

$$Y_t = \varepsilon_t + r_t + u_t \quad (3.22)$$

$$r_t = r_{t-1} + u_t \text{ where } u_t \approx (0, \sigma_u^2) \quad (3.23)$$

Where r_t is a random walk, u_t is $I(0)$ and may be heteroskedastic. Notice that u_t is a pure random walk with innovation variance σ_u^2 . The null hypothesis that y_t is $I(0)$ is formulated as $H_0: \sigma_\varepsilon^2 = 0$. In simpler terms, it tests the null hypothesis that the series is a stationary process against the alternative that the series is not stationary.

This test follows a Lagrange Multiplier (LM) test to assess for stationarity. The LM test is defined as:

$$LM = \frac{\sum_{t=1}^t S_t^2}{\sigma_u^2} \quad (3.24)$$

Decision rule:

1. If LM stat < KPSS critical value, then we do not reject the null hypothesis. This will then imply that the series is stationary
2. If LM stat > KPSS critical value, then we reject the null hypothesis. This then means that the series has a unit root and is not stationary.

In this dissertation, because we are mostly dealing with macroeconomic variables, we are expecting our variables to be non-stationary at their level. In addition to this fact, we were obliged to test whether the variables will be cointegrated or not to proceed either with the VAR or the VECM. However, before we go forward with the cointegration analysis, we first tested for the number of lag lengths that will be suitable for our study.

3.4.6 Determination of the lag structure

The appropriate lag structure is very important when we want to conduct the cointegration test. But estimating the lag length of autoregressive process for a time series is a crucial

econometric exercise in most economic studies (Liew, 2004). It is quite easy and it is based on different information criteria. Criteria such as Akaike information criterion (AIC) (Akaike 1973), Schwarz information criterion (SIC) (Schwarz 1978) and the Hannan-Quinn information criterion (HQ) (Hannan and Quinn 1979) have been used in cointegrated modelling to assist in selecting the lag length of a model from a dataset (Liu, 2007). All of these criterion have been used in different other economic and econometric studies (Liu, 2007; Philbrick & Gustafsson, 2010; Siriwardana et al, 2011) to estimate the appropriate lag length for the selection of a model. The above mentioned criteria (AIC, SIC, HQ) formulas are summarized in Table 3.2 below:

Table 3.2: Information Criteria Selection

Akaike Information Criteria	$-2(L/T) + (K/T)$
Schwarz information criterion	$-2(L/T) + K \log(T) / T$
Hannan-Quinn	$-2(L/T) + 2K \log(\log(T)) / T$

Source: EVIEWS help guide II

where: L is the log of the likelihood function

K is the number of parameters in the model

T is the number of observations

Nonetheless, among these criteria, we cannot access which criterion is the best one. According to literature, SIC is chosen to be the most reliable one but turns out to be inefficient. Conversely, AIC criterion is usually more consistent but turns to be unstable. However, the criterion that gives the lowest information criteria was the one chosen. Nevertheless, Liew (2004) conducted a study to determine which lag length criteria should be chosen when estimating a model. In this study, the author founded out that with a sample of 120 observations and more, the HQ criterion tends to be the most effective one whereas the other criterions appears to be a better choice for smaller samples. He then, concluded that if we want to avoid in choosing too low the lag length, it will be advisable to adopt the AIC and/ or FPE. He also asserted that the gain in choosing these two criteria will be more significant in sample size of not more than 60 observations. So, we clearly noticed that the

choice of the criterion will be dependent on the size of our sample and the best choice of it will be the one that avoid misspecification (autocorrelation, heteroskedasticity, etc...).

3.4.7 Cointegration

Cointegration test is often used as a pre-requisite for determining whether a standard VAR or VECM should be employed to study the relationship between the variables. When cointegration is present in our variables, the VECM will be the appropriate specification to achieve our objectives.

The argument of fake regression and the need to carry out stationarity has been previously discussed. If the stationarity tests discussed above shows the variables are non-stationarity, we will have to take the first differences to correct for non-stationarity. But a first difference on variables throws away the long run properties of the series. Studenmund (2011) therefore called to attention that before the differences should be used; we should first test if the residuals are non-stationary. The author defined this concept of cointegration as a method consisting of matching the degree of non-stationarity of the variables in an equation in a way that makes the residuals of the equation stationary.

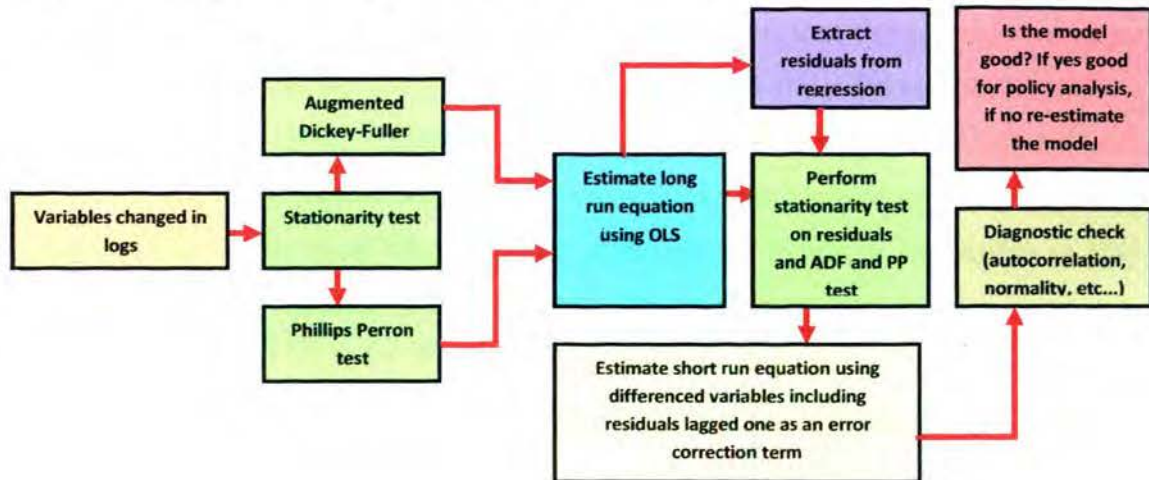
The concept of cointegration was formally introduced by Engle and Granger (1987), and the authors acknowledged that it is a useful method used to examine if non-stationary time series variables are cointegrated. As earlier said, these non-stationary time series will be said cointegrated if the linear combination of these series is stationary. In this light, the stationary linear combinations will be referred to as the cointegrating equations and may be interpreted as the long-run equilibrium relationships (Liu, 2007). We can thus say that the concept of cointegration provides a sound methodology for modelling both long run and short run dynamics in a system (Dunis & Ho, 2005). The concept of cointegration has become very popular and is being used in many economic works and research in this century to overcome the problem of spurious regression encountered with the ordinary least square method. In this way, we realise cointegration is a very important concept that should not be ignored for it allows the researcher to avoid false regression.

As formerly said, the Engle-Granger approach was the first cointegration technique formally introduced by Engle and Granger in 1987. The Engle-Granger method assumed there exists a long run equilibrium relationship within two variables. In other words, we can say this technique accounts for a single long run unique relationship. The two-step procedure of the Engle-Granger cointegration technique is as follows:

1. We will first test for the order of integration of variables using the ADF and PP test
2. The next step will involve testing for cointegration between the variables using an OLS regression. The resulting equation is what will be referred to as the long-run cointegrating equation (equilibrium relationship).
3. From the previous equation, the residuals obtained will be saved and will be tested for stationarity using the ADF test. If the residuals are found stationary at the level, this means that the variables are cointegrated and therefore we confirm the existence of a long run equilibrium relationship among the variables.
4. Lastly, the residuals obtained in the former step will be used to perform a new regression on differenced variables using the OLS. The lagged residual will be incorporated in the regression as a variable and will be referred to as the error correction term. The estimate of the new regression is referred to as the short run relationship. Following the theory, the error correction coefficient should be negative and its value measures the speed of adjustment back to equilibrium when an exogenous shock hits.

For a more detailed and visual inspection of the steps of the Engle-Granger methodology discussed above, we provide the flow chart below:

Figure 3.2: Steps of the Engle-Granger Approach



Though the Engle-Granger methodology is a good method for testing for a unique cointegrating vector, it still presents some drawbacks. The Engle-Granger approach is limited due to its inability to pick out more than one cointegrating vector (one long run relationship). So this means that this method is not reliable and may not produce good and efficient results if we are working with more than two variables. For this reason, applying this technique may infer us to biased results for the fact that we are dealing with eight variables. On the other hand, this method will be used as a separate test in our dissertation to essentially test the existence of a link between household debt and unemployment. This will be done as an isolated investigation from the main data set because of the limitation to the accessibility and access of quarterly unemployment data.

The availability of quarterly unemployment data for the timeline (1985 Q1-2012 Q1) is a restriction. However, we could try and study a selected period using annual data that is available and this we considered it as delimitation. The availability of quarterly unemployment data in South Africa only started in the year 2008. So, it is impossible to perform an analysis because of the low number of observations. For this reason, we employ the Engle-Granger cointegration approach using annual household debt and unemployment data from the period 1980 to 2010 to study the relationship that exists between the two variables.

Conversely, because this approach actually suffers some limitations, we decided to use an alternative approach. The approach is entitled the Johansen Maximum Likelihood procedure.

The main idea behind cointegration is consequently that it offers potential information about the long run equilibrium relationship of the model. It explains that though macro-economic variables may tend to trend up and down over time, groups of variables may drift apart. As a result, econometricians Soren Johansen and Katarina Juselius (1990) formulated estimation and testing procedure for models with one or more cointegrating relationships. When two (or more) variables share the same stochastic and deterministic trends, it is possible to find a linear combination that cancels both the trends. The resulting cointegration relation is not trending, even if the variables by themselves are (Hendry & Juselius, 2000). The Johansen cointegration rank method relies on the cointegrating rank and its characteristic roots.

This approach offers several advantages compared to the Engle-Granger method. With the Johansen procedure, it is possible to find out more one cointegrating relationship because of its ability to deal with more than two variables. This therefore implies that for multivariate studies, it is more useful. Also, compared to the Engle-Granger method, the Johansen procedure provides two tests statistics which can be used to determine the number of cointegrating vectors that exist but with the only inconveniency that they do not always tend to agree. Generally, the Johansen cointegration technique tends to be more problematic in the interpretation when we are dealing with more than one cointegrating relationship. Overall, if this happens, we will have to study carefully which cointegrating equation fits our study.

Nonetheless, the name Johansen cointegration test comes from the fact that the test statistics involved are the trace (the sum of the diagonal elements) of a diagonal matrix of generalized eigenvalues. This test examines the null hypothesis that the cointegration rank is less than or equal to k (which represents the number of variables), against the alternative that the cointegration rank is greater than k . If the trace statistic is greater than the critical value for a certain rank, then the null hypothesis that the cointegration rank is equal to k is rejected. The long-run coefficients (β) are normalised, such that we express the relationship in terms of one of the variables as a dependent variable. The adjustment or short-run parameters (α) can be interpreted the same way as the error correction term t stat are in parentheses and are interpreted the same way as t statistics.

In this study, we performed Johansen's cointegration test to see whether the non-stationary series LRHD, LRHPI, LCPI, LRIN, LRGDP, LRCON and LRSV move together over time and whether cointegration exists among them. Johansen's cointegration test has a null

hypothesis of “no cointegration”. Rejection of the null hypothesis indicates the existence of at least one cointegrating equation. If we found cointegration to exist among the variables, this implies a long run relationship exist and thereby granger causality among them in at least one direction. Consequently, a vector error correction model (VECM) will be used to correct the disequilibrium in the cointegrating relationship captured by the error correction term (ECT).

By employing the Johansen cointegration test, we use both the trace and the max-eigenvalue test to see the number the cointegration equations that exist among our variables. The above tests are summarized by the following equations:

$$\lambda_{max}(r, r + 1) = -T \ln(1 - \lambda_{r+1}) \quad (3.25)$$

$$\lambda_{trace}(r) = -T \ln \sum_{i=r+1}^n (1 - \lambda_i) \quad (3.26)$$

Where λ 's are the estimated eigenvalues of the characteristic equations, T is the number of usable observations and r is the rank of the long-run matrix (π). The number of cointegration vectors (r) is always smaller or equal to the number of endogenous variables (n). The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r + 1$ cointegrating vectors. In implementing the test, we will have to choose either to allow the presence of deterministic trend in the equation or not.

After performing the Johansen cointegration test and concluding that the model has a long run relationship, then it becomes appropriate to say that the variables move together in the short run also. We now proceed with the estimation of the VECM to determine the short run relationship of the variables.

3.4.8 Estimation of the Vector Error Correction Model

In general, when variables are cointegrated, there must also be an error correction model that will describe the short-run adjustments of the cointegrated variables. After showing that the variables are cointegrated and having determined the number of cointegration vectors, the corresponding VECM can be estimated.

According to the Granger Representation theorem, the error correction model is a preferred method for estimation when two integrated time series are statistically related or cointegrated. The vector error correction model, however, is particularly powerful since it allows an analyst to estimate both short term and long run effects of explanatory time series variables. This model is a restricted VAR designed for use with non-stationary series that are definitely identified to be cointegrated. Hassan (2003) described the VECM as a model which describes how the system is adjusting in each time period towards its long run equilibrium state.

The cointegration analysis therefore determined if there is a long run relationship in the variables. Now our main interest is to investigate the short-run movements in the level of household debt using an error-correction model. Hassan (2003) asserted that since there exists a long run relationship among the variables, therefore in the short term, deviations from this long-run equilibrium will feed back on the changes in the dependent variables in order to force their movements towards the long-run equilibrium state. The author then concluded that the coefficients of the error-correction terms derives from the cointegrating vectors represent the proportion by which the long-run disequilibrium in the dependent variables is corrected in each short-term period.

The adjustment process may take a number of periods and thus each equation in the ECM will have lagged variables. It is important to include the appropriate number of lags in the estimation of the VECM.

Sourcing from Naranjo & Toevs (2002), the VECM can be represented as:

$$\Delta X_t = \mu + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \epsilon_t ; t=1, 2, \dots, T \quad (3.27)$$

where

X_t = vector of $p \times 1$ variables

μ = $p \times 1$ vector of intercepts

$\Gamma_1, \Gamma_2, \Gamma_k$ = $p \times p$ vectors of parameters

ϵ_t = error term or vector of impulses representing unanticipated movements in X_t

Δ = difference operator

$I(1)$ = integrated of order one (i.e. first difference stationary)

In the above system, the coefficient matrix Π provides information about the long run relations among the variables, while the matrix Γ provides information on short run relations. Adam and Tweneboah (2008) detailed that the long run coefficient matrix can be written as Π

$=\alpha\beta$ where the β matrix gives the cointegrating vectors, while α gives the amount of each cointegrating vector entering each equation of the VECM, also known as the adjustment matrix.

3.4.9 Diagnostics and Stability Tests

With the VECM already estimated, we now have to test if the estimated equation fits the classical properties of a good model. In other words, we will check if the classical assumptions of a good regression are not violated. The diagnostics and stability tests involve testing the obtained residuals of the VECM. The classical assumptions mentioned above include the following:

- i. No autocorrelation in the error terms
- ii. No heteroskedasticity in the errors terms
- iii. The residuals must be normally distributed
- iv. No multicollinearity in the residuals
- v. The model must be stable.

Therefore, after estimating the VECM, we will check if the estimated model meets all the assumption properties.

3.4.9.1 Autocorrelation

Autocorrelation, also called serial correlation, occurs most frequently in time-series data sets and simply implies that the value of the error term from one period depends in one systematic way on the value of the error term in another time periods (Studenmund, 2011). Testing for autocorrelation is very useful because it helps detect if the estimated model has been subject to misspecification. Autocorrelation often occurs when the residuals are entirely autonomous across observations. Autocorrelation is always present because of some details like some cyclical components, omitted variables, misspecification, etc.

The Durbin-Watson test remains the first common assessment to check for serial correlation in the residuals of the model. Wooldridge (2006) defines the Durbin-Watson (DW) statistics as follows:

$$DW = \frac{\sum_{t=2}^n (\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^n \hat{u}_t^2} \quad (3.27)$$

$$DW \approx 2(1 - \hat{\rho}) \quad (3.28)$$

The DW test is usually computed under the following null versus alternative hypothesis:

$H_0: \hat{\rho} < 0$ and $H_1: \hat{\rho} > 0$

Therefore, to interpret the results is as follows.

1. When $\hat{\rho} \approx 0$, this implies that the DW statistics is close to 2, therefore we conclude there is no serial correlation in the residuals.
2. However, if $DW < 2$ ($DW > 2$), there is positive (negative autocorrelation). Also, when $DW=0$ ($DW=4$), there is perfect positive (negative autocorrelation).

In simpler terms, we can say that if the value of the DW statistic is far from 2, we conclude that serial correlation is present. This test is often unfavourable because it deals only with first order serial correlation. However, this test can only be used when we are dealing with the residuals of an ordinary least square (OLS) regression and cannot therefore be applied to the VECM. The most appropriate tests in our case (since we are dealing with the VECM) will be Langrange Multiplier (LM) test and the Portmanteau autocorrelation test (Bruggemann, Lutkepohl, & Saikkonen, 2004).

The LM and the Portmanteau autocorrelation tests test out for serial correlation in the residuals up to the specified order. The difference with both tests is that the LM test is asymptotically distributed χ^2 with k^2 degrees of freedom whereas the Portmanteau test is distributed χ^2 with degrees of freedom $k^2 (h - p)$ where p is the lag order.

3.4.9.2 Heteroskedasticity

One of the assumptions of a good econometric model is that the error terms have the same variance given any values of the explanatory variables, meaning that the errors are homoscedastic. Therefore, if this assumption does not hold, we can say that the errors are heteroskedastic and the results will not be valid. Consequently, the coefficients estimated and the t and F test will be invalid.

There are several tests to check for heteroscedasticity in the residuals of a model. We can name the Breusch-Pagan (BP) test and the White test. The BP test was proposed by Trevor Breusch and Adrian Pagan while the White test was recommended by Halbert White (1980) and both tests have been extensively used by numerous research and academic papers.

The BP test is used to test heteroskedastidity in a linear regression model. It actually tests whether the estimated variance of the residuals from a regression are dependent on the values of the independent variables (http://en.wikipedia.org/wiki/Breusch%E2%80%93Pagan_test). This test assesses the null hypothesis that the error variances are all equal versus the alternative hypothesis that the error variances are a multiplicative function of one or more variables.

We mention above that the BP test is a test for linear forms of heteroscedasticity. Therefore, it cannot work for non-linear forms of heteroscedasticity. The appropriate test for these non-linear forms is the White test for heteroscedasticity which is the one to be used in this dissertation. The White test is considered in the literature as a special case of the heteroscedasticity. The White test is computed by a regression where we regress the square residuals on all possible cross products of the regressors.

Just like the BP test, the White test tests the null hypothesis of no heteroskedasticity (homoscedasticity) against the alternative hypothesis of heteroscedasticity in the residuals. Mathematically, it is represented as:

$$H_0 = \sigma^2_i = \sigma^2 \text{ For all } i \quad (3.29)$$

$$H_1 = \sigma^2_i \neq \sigma^2 \text{ For all } i \quad (3.30)$$

The White test follows an observed Obs* R-square statistic. This statistic is computed as the number of observations times the R-square (R^2) from the regression. The White test statistic is computed is asymptotically distributed as a chi-square (χ^2) with degree of freedom equal to the number of slope coefficients (excluding the constant) in the test regression. In the software used in this dissertation, that is EVIEWS, there are two alternatives to calculate this test: the cross terms and the no cross terms options (EVIEWS help guide II). According to the literature, the cross term option is the original version of the White test that includes all the

cross product terms while the no cross term option runs the test regression using only squares of the regressors.

3.4.9.3 Normality test

One of the main assumptions of a good regression model is that the residual error terms follow a normal distribution. The normality test used in this dissertation is the Jarque-Bera (JB) normality test. It is a significant test commonly used in the field of economics, statistics, and econometrics, just to name a few to test the null hypothesis that the data sample follows a normal distribution of the skewness being zero and the excess kurtosis being zero. The JB test works out the skewness and kurtosis measures of the model residuals and thus utilizes the following statistic:

$$JB = \frac{n}{6} \left(S^2 + \frac{1}{4} (K - 3)^2 \right) \quad (3.31)$$

where n represents the number of observations (or degree of freedom), S is the sample skewness and K is the sample Kurtosis.

The JB statistic asymptotically has a χ^2 distribution with two degree of freedom. Nevertheless, it should be noted that this diagnostic test is not a very important condition especially when we want to deal with forecasts. It was acknowledged that this test is very sensitive with the number of observations (Stengos & Wu, 2006).

3.4.9.4 Stability test

As earlier said, when estimating a model, it is very important to check if the model fits to the assumptions properties of a classical model. The Stability test is a very important one among one of them. According to Assenmacher-Wesche (2008), the stability test of the VAR is a diagnostic test use to check if the estimated model meets the stability properties of a good model. This test was chosen because it has be shown in several papers to be the ideal test to examine if a particular estimated model is stable.

The AR inverse Roots table/graph is the test used in our study to check if our estimated VECM is stable. The results of the test can either be presented in the form of a table or a graph. After computing the test in the form of a graph, we can only conclude that the estimated VECM is stable (stationary) if all roots have modulus less than one and lie inside

the unit circle (EViews7 User's Guide II) . However, if the model is not stable, certain results (such as impulse response standard errors) are not valid.

In mathematical form, the necessary and sufficient condition for stability is expressed as follows:

- ◆ Inside unit circle
 - ★ Necessary condition: $\sum_{i=1}^n a_i < 1$
 - ★ Sufficient condition: $\sum_{i=1}^n |a_i| < 1$
- ◆ Unit root process
 - ★ Unit root exit, if $\sum_{i=1}^n a_i = 1$

After all the diagnostic tests are performed and the model fits all the classical properties, we can proceed with the dynamic analysis of the model. The dynamic effect of VECM is conveniently analysed by the variance decomposition and impulse response function (IRF/GIRF). The importance of these two analyses is that they are very good at forecasting.

3.4.10 Variance Decomposition Analysis

Also called the Forecast Variance Decomposition, the Variance Decomposition essentially denotes to the breakdown of the forecast error variance for a particular time horizon. It measures the contributions of each type of shocks to the forecast error variance. It is essentially aid to understand more the importance of the parameters in our estimated model. The Variance Decomposition separates the variation in an endogenous variable into the component shocks to the VAR/VECM. In other words, the Variance Decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR/VECM (Ludi & Ground, 2006; Georgantopoulos, 2012). The Variance Decomposition has the power to tell us which variables in the model has short term or long term impacts on another variable of interest (<http://espin086.wordpress.com/2011/04/>).

Thus, we conclude by saying that the main aim to conduct the Variance Decomposition is obtain information about the relative significance of each random innovation in affecting the variables in the VAR.

3.4.11 Generalized Impulse Response Functions

A shock to the i -th variable do not only directly affects the i -th variable but is also transmitted to all of the other endogenous variables through the dynamic (lag) structure of the VAR/VECM (Akanbi, 2011; Moniruzzaman, Toy, Hassan, 2011). An impulse response function traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. In other terms, the IRF_s together with the GIRF_s show the effects of shocks on the adjustment path of the variables. This analysis is very useful especially when we want to access how shocks to economic variables resound through a system. However, if the innovations are contemporaneously uncorrelated, interpretation of the impulse response is straightforward. The i -th innovation is simply a shock to the i -th endogenous variable. Prabir De and Neogi (2011) asserted that the innovations are usually correlated so that they have a common component which cannot be associated with a specific. In order to interpret the impulses, it is common to apply a transformation to the innovations so that they become uncorrelated.

Applying this investigation on a given model will be very good but nevertheless, it presents some drawbacks. Firstly, the results of the IRF are strongly affected by the ordering of the variables. This indicates that to get reliable and good results, we should order our variables properly and this might be a very difficult task. Consequently, many researchers did overcome this difficulty by using the GIRF proposed by Pesaran and Shin (1998) which offers a partial solution and effectively describe the dynamics in a time-series model by mapping out the reaction of one variable to a one standard deviation shock to the residuals in the equation. The GIRF has been utilized by many other studies (Warne, 2008; Mukuddem-Petersen *et al.*, 2010; Peng *et al.*, 2011, Niblock & Harrisson, 2012) and has been postulated to be more powerful than the simple IRFs. The GIRF does not take into account the ordering of the variables as compared to the previous one. As a result, the result estimates are more valid and consistent because it is not affected by the manner our variables will be ordered. Nevertheless, another critique of the IRF is the omission of variables. Omitting important variables in the model may lead to major distortions in IRF and make the empirical results worthless (Lin, 2006).

The GIRF will therefore be explained in this study because we can construct an orthogonal set of innovations that are indifferent to the ordering of the variables. More robust results are expected with the computation of the GIRFs compared to using the ordinary IRFs.

Finally, we conclude that while IRFs trace the effects of a shock to one endogenous variable onto the other variables in the VAR/VECM, the Variance Decomposition shows which shocks contributes the most in affecting the rest of the variables in the VAR.

This chapter has described all the steps followed when investigating the main reasons why households record high debt levels in South Africa. Also, it explained the tests that were used to examine the impact of the 2008-2009 financial crisis on Household debt. In the sequel, the results of our analysis are presented in Chapter 4.

CHAPTER 4

EMPIRICAL RESULTS AND INTERPRETATION

“Absence of evidence is not evidence of absence”

Carl Sagan

4.1. INTRODUCTION

4.2. DESCRIPTIVE STATISTICS

4.3. VISUAL INSPECTION OF THE VARIABLES

4.4. STATIONARITY TEST

4.5. LAG LENGTH DETERMINATION CRITERIA

4.6. JOHANSEN COINTEGRATION TEST

4.7. ESTIMATION OF THE VECM

4.8. DIAGNOSTIC TESTS OF THE VECM

4.9. DISCUSSION OF THE RESULTS

4.10. DYNAMIC ANALYSIS

4.11. RELATIONSHIP BETWEEN HOUSEHOLD DEBT AND UNEMPLOYMENT

4.1 INTRODUCTION

In the previous chapter, we presented the modeling strategy and the associated econometric tests that were employed in this dissertation using the EVIEWS statistical computer software package. In this section, we present the results and the interpretation of the different tests conducted in this study. We gradually followed the detailed steps (see Figure 3.1) described in the previous chapter in order to reach our main aims for this dissertation. The rationale of this research is to understand why the household debt sector records high debt levels in South Africa. In addition, we tried to identify to what level the 2008-2009 financial crisis affected household debt and related macroeconomic determinants. In this context, our first step is the analysis of the descriptive statistics which provides information about the characteristics of the sample under study. The next step is the graphical inspection of our time series to examine the interdependence between the variables and to determine to what extent the 2008-

2009 financial crisis played a role in the rise and fall of these variables. Subsequently, we performed the stationarity test to check the order of integration. Thereafter, the appropriate lag length used in this dissertation was tested and then we proceeded with the Johansen cointegration test. A complete VECM was estimated by imposing the restrictions needed. Then, some diagnostic and stability tests were done to ensure the robustness of our estimated model. The Variance Decomposition and the GIRF were estimated to capture how the time series variables (containing quarterly data from 1985Q1-2012 Q1) are affected due to exogenous shocks.

Previously, in chapter 3 we mentioned the limitations of this dissertation due to the inaccessibility of quarterly unemployment data. Therefore, after completing the analysis with our main data set, we proceeded with a separate analysis of the Engle-granger methodology. We used the Engle-granger cointegration technique to identify if household debt and unemployment are closely related in the South African case. Unlike our main analysis household debt and unemployment was investigated using annual from the period 1980-2010.

Before we started our analysis, all our variables were transformed into natural logarithms to avoid some misspecification problems in the course of our study. The main variables analyzed in this study were the natural log of real household debt (LRHD) which acts as the dependent variable, natural log of real house price index (LRHPI), natural log of Consumer price Index (LCPI), natural log of real income (LRIN), natural log of real prime rate (LRPR), natural log of real Gross Domestic product (LRGDP), natural log of real household consumption (LRCON) and natural log of real household savings (LRSV).

4.2 DESCRIPTIVE STATISTICS

Before starting the econometric analysis, we described our dataset by presenting the descriptive statistics of our variables. In particular, we described the main features of the data used in this dissertation. Our complete set of variables consists of 109 observations ranging from 1985Q1 to 2012Q1. In the descriptive statistics described in Table 4.1, we present the mean, median, the standard deviation, the skewness, the kurtosis and the Jarque-Bera statistics. Our main concentration on these statistics was mainly on the skewness and kurtosis because it assists to immediately determine if the data follows a normal distribution. As we

explained previously in chapter 3, normal distribution is a key assumption when using statistical techniques. All the variables show a positive skewness except for CPI and savings which indicate a negative skewness. The positive skewness shows that the distribution is skewed to the right. On the other hand, the main aim of the kurtosis is to see the flatness or the peakness of the distribution (O'Neil, 2009). The value of the kurtosis for all the variables is less than 3 which means that the distribution is flat. For all the variables except for prime rate, all the variables show forms of non-normality with a p-value less than 5%. Nevertheless, it was acknowledged that the normality test is very sensitive to the number of observations and may only produce desirable and efficient results if observations are large. As cited in O'Neil (2009), Field (2009) affirmed that the significance tests of the skewness and kurtosis should be with large samples because they are likely to be significant even when skew and kurtosis are not too different from normal.

Table 4.1: Summary of the Descriptive Statistics of the Variables

	LRHD	LRHPI	CPI	LRIN	LRPR	LRGDP	LRCON	LRSAY
Mean	4.803	4.018	3.900	13.717	3.420	14.186	14.278	4.9752
Median	4.675	3.819	4.050	13.661	3.572	14.094	14.090	9.112
Maximum	6.117	4.679	4.799	14.232	5.319	14.762	15.313	11.135
Minimum	4.118	3.600	2.504	13.244	2.002	13.762	13.859	-10.099
Std. Dev.	0.521	0.366	0.629	0.304	0.805	0.314	0.391	7.854
Skewness	0.788	0.679	-0.546	0.193	0.092	0.391	1.073	-1.141
Kurtosis	2.617	1.789	2.252	1.731	2.134	1.745	2.947	2.403
Jarque-Bera	11.952	15.043	7.966	7.991	3.558	9.943	20.945	25.296
Probability	0.002	0.000	0.018	0.018	0.168	0.006	0.000	0.000
Sum	523.53	438.02	425.15	1495.19	372.819	1546.335	1556.40	542.301
Sum Sq. Dev	29.375	14.543	42.779	10.025	69.992	10.687	16.512	6663.37
Observations	109	109	109	109	109	109	109	109

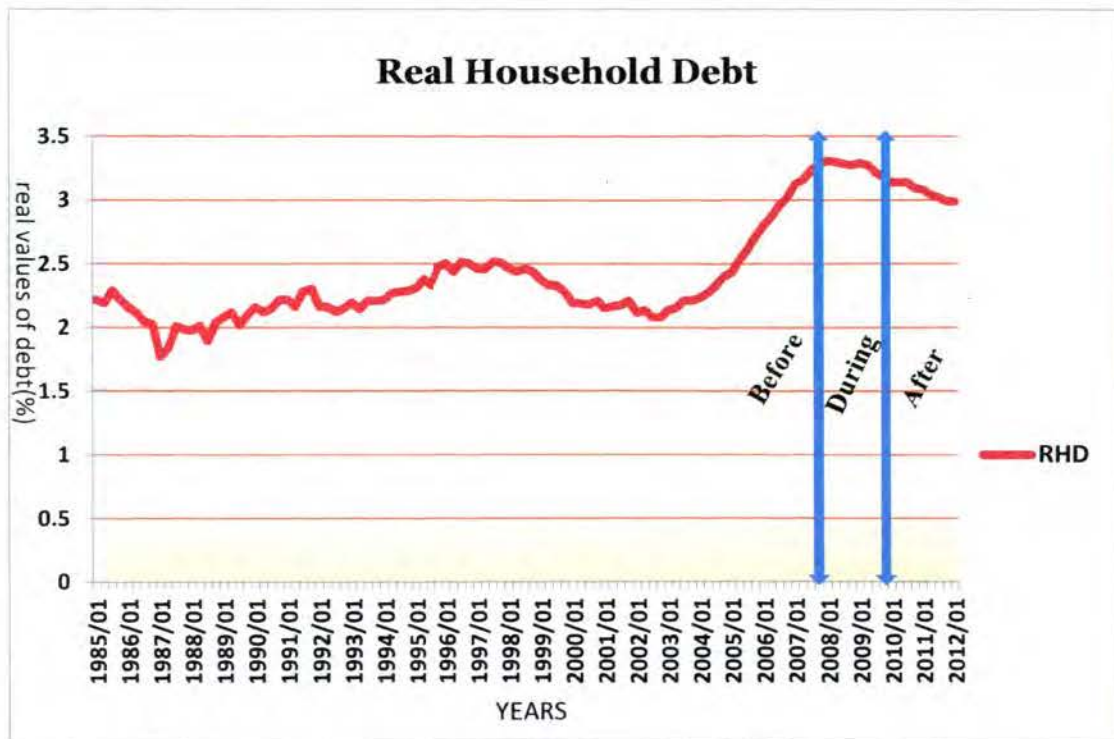
Having presented the descriptive statistics of our variables, we will now proceed with the visual inspection of the data.

4.3 VISUAL INSPECTION OF THE VARIABLES

As previously mentioned, the main variables used in this study are LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON and LRSAV. The principal reason why we proposed this visual inspection is to analyze and visually examine the possible trends in the South African household debt level in relation to the period “before”, “during” and “after” the 2008-2009 financial crisis. In this regard, we were able to examine the fluctuations of household debt levels in the country and check if it was affected by the 2008-2009 recent economic meltdowns. Also, we inspect the trend of the related variables considered to be the determinants of increasing household debt levels in South Africa. The graphical inspection of the time series will also benefit us in identifying the nature of the variables. Specifically, we will easily be able to detect if the time series are stationary at their level or after their first difference. Ultimately, the visual inspection provides a first impression of what to expect from the outcome of the stationarity test.

In Figure 4.1, we graphical represent household debt to examine its trend period “before”, “during” and “after” the 2008-2009 financial crisis.

Figure 4.1: Graphical Analysis of Household Debt



In Figure 4.1, we divide the graph in different segments/zones to analyze the periods “before”, “during”, and “after” the 2008-2009 financial crisis. In general, the period “before” the crisis (1985Q1 to 2007Q2) reveals that household debt steadily increases. From the year 02Q1 until 07Q2, the household debt experienced a drastic increase. A decrease in debt level is evident in the period “during” the crisis which includes the period 07Q3 to 09Q4. This represents an insignificant decline in the level of household debt that still continues to be very high. We think that this slight decrease in household debt is due to several reasons related to stricter banking regulations. In this context, banks became more conservative regarding lending. Also, the implementation of the National Credit Act (NCA) in 2007 could have influenced this decline. The main purpose of the NCA in South Africa was to protect consumers against over-indebtedness, exploitation and manipulation by the informal sector. Finally, the financial meltdown together with the South African recession possibly influenced household’s borrowing behavior. In this context, many households became more conservative and eager to consolidate their debt rather than make new debt.

After the crisis (from 2010 to date), the debt level continues to drop slowly. Nevertheless, household debt levels continue to be very high compared to preceding years. The 2008-2009 crisis affected the level of household debt to a lesser extent compared to other countries in the world (especially the US and Europe). Nevertheless, this impact is still significant and contrary to some earlier predictions, that South Africa will not be affected by this crisis.

In, Figures 4.2 and 4.3 we present the graphical analysis of our logged variables at level and at their first difference respectively, whereby we will capture the possible trends and nature of the variables.

Figure 4.2: Graph of Variables at their Level

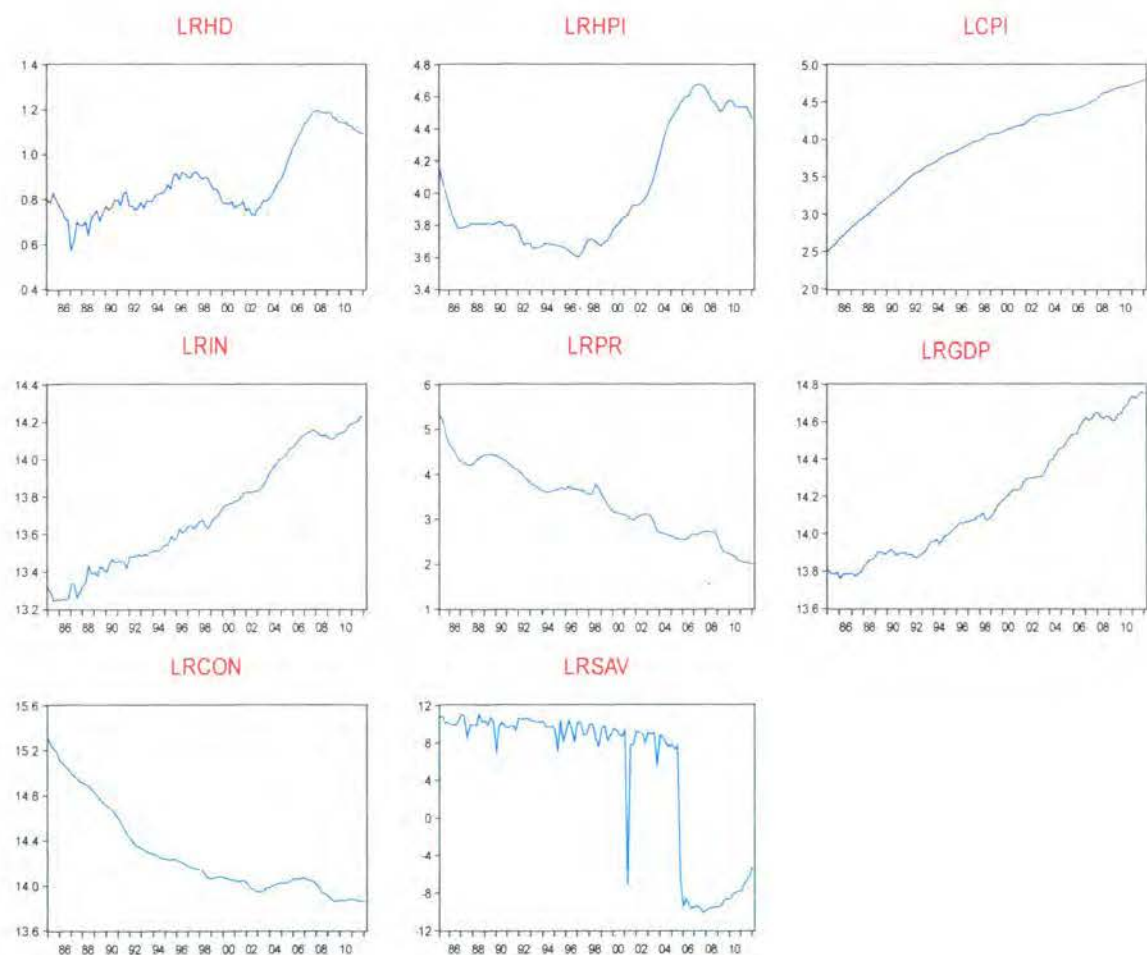
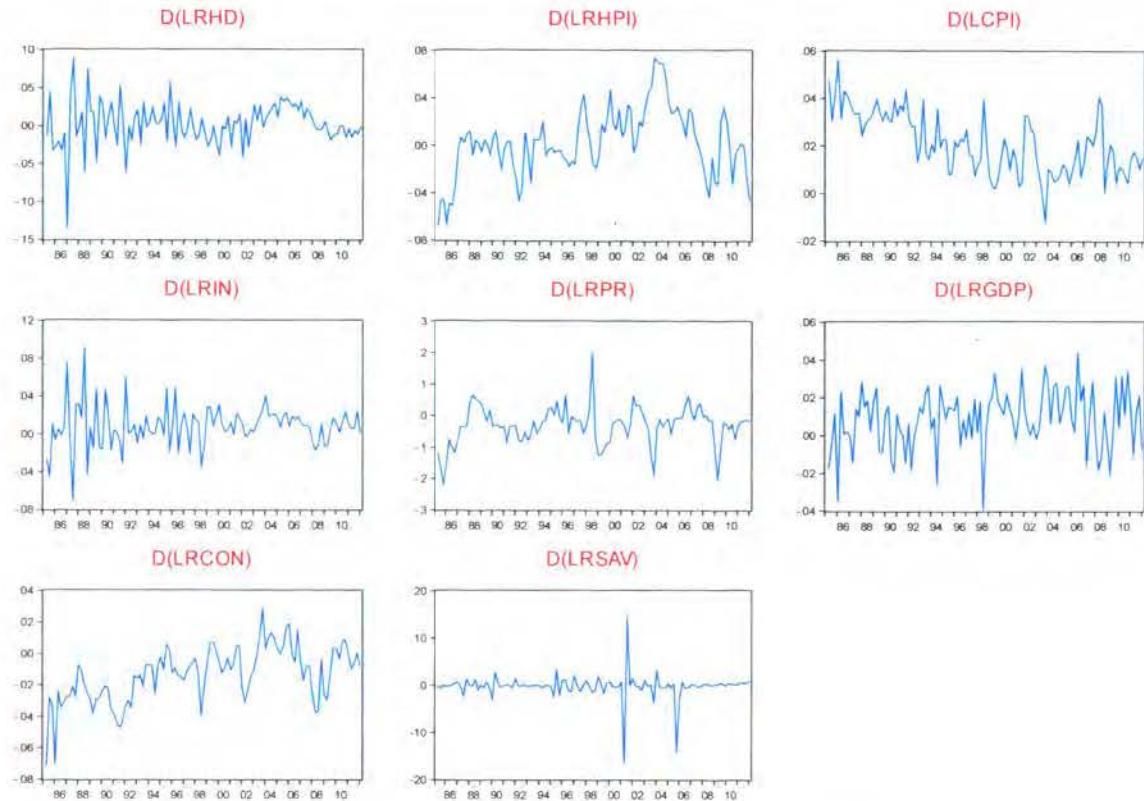


Figure 4.3: Graph of Variables at their First Difference



As alluded earlier, Figures 4.2 and 4.3 show the visual inspection of the variables at their level and at their first difference, respectively. The visual examination of the data revealed that LRHD, LCPI, LRIN and LRGDP confirm similar trend. At the initial point, they increase and continue to progressively increase at an increasing rate.

Clearly, the series are trending upwards; which entail increasing over time. When we look at the period “before”, “during” and “after” the crisis, the variables did not really change because from the graph, we note they continuously increase at an increasing rate. Therefore, we can conclude that the 2008-2009 financial crisis together with other crises that occurred before did not have any significant effect on the movement of these variables. Again, seeing that they are all trending upwards, we can postulate that they are non-stationary at their level and will need to be differenced to make it stationary.

On the other hand, we see that LRPR and LRCON show a different trend compared to the others. These variables indicate a downward fluctuating behaviour characterised by slight fluctuations. We can easily see that the period preceding the 2008-2009 crisis did not have

significant effects on the two variables because a dramatic alteration is not observed within that period.

The variable LRHPI reveals a significant upward trend. We actually noticed a dramatic increase in house price from the year 2000-2007. The variable reached its peak in the year 2007 and after that year, it began to diminish till present. These movements could be assigned to the 2007 house price bubble that originated in America. Consequently, we propose that the burst of house prices that happened in America in 2007 slightly affected house prices in South Africa.

LRSAPV appears to have a stable movement up to the year 2000. From the visual inspection, we noticed significant movements from the year 2000. Savings in South Africa appears to be affected by the 2008-2009 financial crisis. Evidently, we identified a sharp decrease in the variable in the year 2006 but it started to recover slowly after the year 2007.

Clearly, all these variables appeared to be trended, hence non-stationary at their level. The series needed to be differenced to remove the trend. Figure 4.3 shows the variables transformed at the differenced level and generally, all the variables appeared to be stationary. The variables show no more trending behaviour and seem to be invariant in time. Finally, we support through a visual inspection of our variables that they all appeared to be non-stationary at their level and after differencing them, they are stationary. This conclusion will be confirmed with the unit test results analysed in the following section.

4.4 STATIONARITY TEST

The estimation of the VECM implies that the variables used should be non-stationary at their level. Therefore, it is appropriate to check for the order of integration of our time series variables. Many studies have indeed showed that many variables especially macroeconomic variables are expected to be non-stationary at their level (Babatunde & Adebafi, 2005; Martins, 2010). It was concluded and later became evident in the literature that performing a regression on non-stationary variables will probably lead us to misleading results. Consequently, it is important to first test for the order of integration before we proceed any further with our analysis.

In this dissertation, we perform three stationarity tests to determine the order of integration of our variables. The ADF and PP test with a constant, constant and trend and none of the above are utilized to check if our variables are stationary. The KPSS test for stationarity is also employed to confirm the results of the other two tests. The results of the ADF, PP and KPSS tests followed by the relevant critical values, as well as the number of lags to get rid of serial correlation, are provided in Tables 4.2, 4.3 and 4.4 respectively.

4.4.1 The ADF test

The purpose of this test is to look at whether the data is stationary at their level or after their first difference. We test the null hypothesis of whether the time series has a unit root against the alternative hypothesis that it does not have a unit root.

With the results provided in Table 4.2, we reject the null hypothesis if the ADF test statistics is greater than the critical value at a particular significance level.

Table 4.2: ADF Unit Root Test Results

Variable	Level of test	Model	Number of lags	ADF test statistics	5% critical value	10% critical value	Order of integration
LRHD	Level	Intercept	0	-0.517	-2.888	-2.581	
		Trend + intercept	6	-2.694	-3.452	-3.152	
		None	0	0.881	-1.944	-1.615	I(0)
	Difference	Intercept	0	-10.491	-2.888	-2.581	I(1)**
		Trend + intercept	0	-10.489	-3.452	-3.152	I(1)**
		None	2	-4.567	-1.944	-1.615	
LRHPI	Level	Intercept	1	-1.109	-2.888	-2.581	
		Trend + intercept	1	-1.877	-3.452	-3.152	
		None	1	0.456	-1.944	-1.615	I(0)
	Difference	Intercept	0	-3.578	-2.888	-2.581	I(1)**
		Trend + intercept	0	-3.444	-3.452	-3.152	I(1)**
		None	0	-3.547	-1.944	-1.615	
LCPI	Level	Intercept	1	-4.312	-2.888	-2.581	I(0)
		Trend + intercept	1	-2.919	-3.452	-3.152	
		None	1	3.022	-1.944	-1.615	I(0)
	Difference	Intercept	0	-4.788	-2.888	-2.581	
		Trend + intercept	0	-6.201	-3.452	-3.152	I(1)**
		None	2	-1.747	-1.944	-1.615	
LRIN	Level	Intercept	0	0.369	-2.888	-2.581	I(0)
		Trend + intercept	0	-3.362	-3.452	-3.152	
		None	0	3.961	-1.944	-1.615	I(0)
	Difference	Intercept	0	-11.437	-2.888	-2.581	
		Trend + intercept	0	-11.426	-3.452	-3.152	I(1)*
		None	0	-9.886	-1.944	-1.615	
LRPR	Level	Intercept	1	-1.270	-2.888	-2.581	
		Trend + intercept	1	4.617	-3.452	-3.152	I(0)
		None	1	2.466	-1.944	-1.615	I(0)
	Difference	Intercept	0	-5.254	-2.888	-2.581	I(1)**
		Trend + intercept	0	-5.245	-3.452	-3.152	
		None	0	-4.688	-1.944	-1.615	
LRGDP	Level	Intercept	0	1.540	-2.888	-2.581	I(0)
		Trend + intercept	0	-2.345	-3.452	-3.152	
		None	0	5.872	-1.944	-1.615	I(0)
	Difference	Intercept	0	-9.286	-2.888	-2.581	
		Trend + intercept	0	-9.480	-3.452	-3.152	I(1)**
		None	3	-2.647	-1.944	-1.615	
LRCON	Level	Intercept	1	-3.330	-2.888	-2.581	I(0)
		Trend + intercept	1	-1.946	-3.452	-3.152	
		None	1	-2.725	-1.944	-1.615	I(0)
	Difference	Intercept	0	-4.985	-2.888	-2.581	
		Trend + intercept	0	-5.730	-3.452	-3.152	I(1)**
		None	0	-5.729	-1.944	-1.615	
LRSAY	Level	Intercept	1	-1.062	-2.888	-2.581	
		Trend + intercept	1	-2.231	-3.452	-3.152	
		None	1	-1.336	-1.944	-1.615	
	Difference	Intercept	0	-14.578	-2.888	-2.581	I(1)**
		Trend + intercept	0	-14.524	-3.452	-3.152	I(1)**
		None	0	-14.580	-1.944	-1.615	I(1)**

*indicates significance at 5% ** indicates that it is significant at 10%

The number of lags was calculated using the Schwartz Information Criteria (SIC). From the results, we noticed that at the models of “none”, almost all the variables are stationary at their levels (I (0)) except for LRHD, LRHPI and LRSAV. Also, concerning the models of “intercept”, all variables appear to be non-stationary except for LCPI and LRCON. Nevertheless, we see an exceptional where the variable LRSAV is found to be non-stationary at all models. The stationarity characteristics of these variables can be confirmed with the absolute values of their ADF t-statistics greater than the absolute of the critical values at the given significance level.

When we look at the model of intercept and trend, it emerges that all the variables are non-stationary at the level since the absolute values of the ADF test statistics is less than the absolute critical value at all significance levels. Therefore, we do not reject the null hypothesis that there exists a unit root. As a result, we needed to conduct the test at their difference level. From the results, we notice that after the first difference test, the absolute value of the ADF test statistics is seen to be greater than the absolute critical values at all significance levels which therefore confirms that the series are stationary after differencing them once. Consequently, we postulate that at the model of intercept and trend, all the time series contain a unit root and are seen to be I(1). This model is seen to be more realistic than the other two models (intercept and none) because it confirms the results of our graphical analysis.

Since the ADF test is subject to many critiques for having low power to reject the null hypothesis when in fact it is false (Seddighi, Lawler & Katos, 2000), therefore, we decide to use another test to back up our results.

4.4.2 The PP test

Similarly to the ADF test, the PP tests the null hypothesis that time series contain a unit root against the alternative hypothesis that the series does not contain a unit root. The result of this test is provided in Table 4.3 and its interpretation is identical to the ADF test. The null hypothesis is rejected if the ADF test statistics is greater than the critical value at a particular significance value.

Table 4.3: PP unit root test results

Variable	Level of test	Model	Bandwidth	PP test statistics	5% critical value	10% critical value	Order of integration
LRHD	Level	Intercept	6	-0.768	-2.888	-2.581	
		Trend + intercept	6	-2.159	-3.452	-3.152	
		None	6	0.696	-1.944	-1.615	I(0)**
	Difference	Intercept	6	-10.632	-2.888	-2.581	I(1)**
		Trend + intercept	6	-10.621	-3.452	-3.152	I(1)**
		None	6	-10.609	-1.944	-1.615	
LRHPI	Level	intercept	8	-0.501	-2.888	-2.581	
		Trend + intercept	7	-2.571	-3.452	-3.152	
		None	7	0.44	-1.944	-1.615	I(0)**
	Difference	intercept	6	-3.438	-2.888	-2.581	I(1)**
		Trend + intercept	6	-3.170	-3.452	-3.152	I(1)**
		None	6	-3.416	-1.944	-1.615	
LCPI	Level	intercept	5	-6.855	-2.888	-2.581	I(0)
		Trend + intercept	4	-3.574	-3.452	-3.152	I(0)
		None	8	5.515	-1.944	-1.615	I(0)
	Difference	intercept	4	-4.646	-2.888	-2.581	
		Trend + intercept	3	-6.171	-3.452	-3.152	
		None	3	-2.236	-1.944	-1.615	
LRIN	Level	intercept	2	0.534	-2.888	-2.581	I(0)**
		Trend + intercept	5	-3.391	-3.452	-3.152	I(0)**
		None	2	4.551	-1.944	-1.615	I(0)**
	Difference	intercept	2	-11.632	-2.888	-2.581	
		Trend + intercept	2	-11.617	-3.452	-3.152	
		None	6	-10.094	-1.944	-1.615	
LRPR	Level	intercept	6	-1.638	-2.888	-2.581	
		Trend + intercept	6	-4.075	-3.452	-3.152	I(0)
		None	6	-3.548	-1.944	-1.615	I(0)
	Difference	intercept	2	-5.173	-2.888	-2.581	I(1)**
		Trend + intercept	2	-5.172	-3.452	-3.152	
		None	1	-4.678	-1.944	-1.615	
LRGDP	Level	intercept	5	1.302	-2.888	-2.581	I(0)**
		Trend + intercept	5	-2.283	-3.452	-3.152	
		None	5	4.987	-1.944	-1.615	I(0)
	Difference	intercept	5	-9.361	-2.888	-2.581	
		Trend + intercept	5	-9.521	-3.452	-3.152	I(1)**
		None	7	-8.115	-1.944	-1.615	
LRCON	Level	intercept	7	-5.205	-2.888	-2.581	I(0)
		Trend + intercept	7	-2.718	-3.452	-3.152	
		None	7	-3.815	-1.944	-1.615	I(0)
	Difference	intercept	6	-5.006	-2.888	-2.581	
		Trend + intercept	5	-5.888	-3.452	-3.152	I(1)**
		None	5	-4.059	-1.944	-1.615	
LRSAY	Level	intercept	2	-1.289	-2.888	-2.581	
		Trend + intercept	4	-2.775	-3.452	-3.152	
		None	1	-1.517	-1.944	-1.615	
	Difference	intercept	3	-15.076	-2.888	-2.581	I(1)**
		Trend + intercept	3	-15.037	-3.452	-3.152	I(1)**
		None	2	-14.899	-1.944	-1.615	I(1)**

*indicates that it is significant at 5%

** indicates that it is significant at 10%

The ADF test result conducted previously showed that the model of “intercept and trend” appeared to be more realistic than the others. In this regard, we still observe the great importance of this model from the PP test outcome. The PP test results reveal that at the model of “intercept and trend”, all the variables are found to be $I(1)$ with the exception of LCPI, LRIN (at 10%) and LRPR. Interestingly, LCPI is seen to be stationary at all models. The stationarity of this variable however, does not match with its graphical analysis as seen in Figure 4.2. We conclude that the “trend and intercept” model is more significant than the other two models and confirm that the time series variables are all $I(1)$ except for LCPI, LRIN and LRPR.

4.4.3 The KPSS test

Compared to the ADF and PP test described above, the KPSS tests the null hypothesis that the series does not contain a unit root beside the alternative that the series contains a unit root. The null hypothesis that the series does not contain a unit root will be rejected if the KPSS statistics is greater than the critical value. The result of the KPSS is shown in Table 4.4.

Table 4.4: KPSS unit root test results

Variable	Level of test	Model	Bandwidth	LM test statistics	5% critical value	10% critical value	Order of integration
LRHD	Level	Intercept	9	0.799	0.463	0.347	
		Trend + intercept	8	0.143	0.146	0.119	I(0)*
	Difference	Intercept	6	0.123	0.463	0.347	I(1)**
		Trend + Intercept	6	0.075	0.146	0.119	
LRHPI	Level	Intercept	9	0.810	0.463	0.347	
		Trend + intercept	9	0.257	0.146	0.119	
	Difference	Intercept	8	0.407	0.463	0.347	I(1)**
		Trend + intercept	7	0.179	0.146	0.119	
LCPI	Level	Intercept	9	1.161	0.463	0.347	
		Trend + Intercept	9	0.285	0.146	0.119	
	Difference	Intercept	8	0.950	0.463	0.347	
		Trend +intercept	6	0.224	0.146	0.119	
LRIN	Level	Intercept	9	1.179	0.463	0.347	
		Trend + Intercept	8	0.193	0.146	0.119	
	Difference	Intercept	1	0.131	0.463	0.347	I(1)**
		Trend +intercept	2	0.065	0.146	0.119	I(1)**
LRPR	Level	Intercept	9	1.200	0.463	0.347	
		Trend + Intercept	7	0.037	0.146	0.119	I(0)**
	Difference	Intercept	6	0.112	0.463	0.347	I(1)**
		Trend +intercept	6	0.067	0.146	0.119	
LRGDP	Level	Intercept	9	1.165	0.463	0.347	
		Trend + Intercept	8	0.290	0.146	0.119	
	Difference	Intercept	6	0.373	0.463	0.347	I(1)*
		Trend +intercept	5	0.074	0.146	0.119	I(1)**
LRCON	Level	Intercept	9	1.041	0.463	0.347	
		Trend + Intercept	9	0.284	0.146	0.119	
	Difference	Intercept	8	0.806	0.463	0.347	
		Trend +intercept	7	0.136	0.146	0.119	I(1)*
LRSV	Level	Intercept	9	0.838	0.463	0.347	
		Trend + Intercept	8	0.229	0.146	0.119	
	Difference	Intercept	5	0.083	0.463	0.347	I(1)**
		Trend +intercept		0.056	0.146	0.119	I(1)**

*indicates that it is significant at 5%

** indicates that it is significant at 10%

The results of the KPSS show that all the variables are integrated of order one at the model of intercept and trend except for LRHD, LRHPI, LCPI and LRPR. We noticed that even after taking the first difference of the variable LCPI, it was still shown to be non-stationary. So we assume this variable is probably an $I(2)$ variable when we consider this test. However, LRPR and LRHPI are shown to be stationary after first difference only at the model of intercept.

Except for the variable LCPI, the three tests confirm the strength of the order of integration of our time series variables. But looking at the graphical inspection of the variable, it seems to be increasing over time thus confirming the existence of a unit root. The ADF test confirms that the variable is $I(1)$ while the other two tests did not. We will proceed with our estimation considering that LCPI is $I(1)$ because at least one of the tests tells us that it is and it is further confirmed with the uniformity of the visual inspection.

As previously stated, to perform the VECM the time series data needed to be stationary. This condition is therefore satisfied since our variables were seen to be integrated of the same order ($I(1)$). Accordingly, we can now proceed with the cointegration test.

Before we proceed with the cointegration test, the next step is to determine the appropriate lag length suitable for the estimation of the cointegration test.

4.5 LAG LENGTH DETERMINATION TEST

The suitable number of lags to use is very vital in time series analysis. When defining a VECM, it is necessary to identify the number of lags that will best suit the model. With the appropriate lag structure, we can easily avoid misspecification problems such as autocorrelation. We use the likelihood ratio (LR), the Final Prediction Error (FPE), the Akaike Information Criteria (AIC), the Schwarz information criterion (SIC) and the Hannan-Quinn information criterion (HQ) to determine which lag will be significant in this dissertation. Based on the estimation of a VAR, the results are reported in Table 4.5.

Table 4.5: Lag length determination criteria results

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	589.7853	NA	1.37e-15	-11.52050	-11.31336	-11.43664
1	1821.658	2244.204	1.24e-25	-34.64669	-32.78245*	-33.89199
2	1947.212	208.8421	3.76e-26*	-35.86558	-32.34423	-34.44004*
3	1998.127	76.62483	5.16e-26	-35.60647	-30.42802	-33.51009
4	2047.239	66.13114	7.78e-26	-35.31166	-28.47610	-32.54443
5	2117.043	82.93486	8.45e-26	-35.42658	-26.93392	-31.98851
6	2203.120	88.63401*	7.49e-26	-35.86376	-25.71398	-31.75484
7	2273.586	61.39618	1.07e-25	-35.99180	-24.18492	-31.21203
8	2376.931	73.67153	1.02e-25	-36.77090*	-23.30692	-31.32029

* 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

SIC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Choosing the specification with the lowest information gives us 6 lags for LR, 2 lags for FPE and HQ, 8 lags and 1 lag for SIC. In order to tackle the problem of autocorrelation, we decided to use two lags. However, adding also too many lags may not solve the autocorrelation problem. But our conclusion is that since we are dealing with quarterly data, it will be preferable to use at least 2 lags to avoid some misspecification.

Having identified which lag will best suit our study, we now proceeded with the cointegration test.

4.6 JOHANSEN COINTEGRATION TEST

This section is aimed at investigating the long term relationship between household debt and other macro-economic determinants by utilizing the Johansen cointegration test. As explained in chapter 3, we used the Johansen instead of the Engle-granger because we could easily capture if there exist more than one cointegrating relationship of which the latter cannot. One

condition of using this test is that the time series variables should be integrated of the same order. Our study fully satisfies this condition where all our variables were found to be integrated of order one. Therefore, the purpose of this test is to be able to recognize if cointegration exists among the variables and the number of cointegration equations that exists. Cointegration test is therefore very important because its outcome will easily tell us if we should proceed with a VAR or a VECM.

We performed Johansen's cointegration test to see whether the non-stationary LRHD, LRHPI, LCPI, LRIN, LRPR, LRCON and LRSAV move together over time and whether cointegration exists among them. If we found cointegration to exist among the variables, this implies a long run relationship exist and thereby Granger causality among them in at least one direction. Consequently, a vector error correction model (VECM) will be used to correct the disequilibrium in the cointegrating relationship captured by the error correction term (ECT).

Table 4.6 reports the results of the Johansen cointegration test performed by using EVIEWS.

**Table 4.6: Cointegration test with linear deterministic trend and 2lags
(Intercept (no trend in CE) and test VAR)**

ENDOGENOUS SERIES: LRHD, LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON, LRSAY						
Lags in VAR: 2						
Number of observations after adjustments: 106						
Trend assumption: Linear deterministic trend						
Hypothesized No of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Hypothesized No of CE(s)	Max- Eigen Statistic	0.05 Critical value
None *	0.477041	226.9401	159.5297	None *	68.71474	52.36261
At most 1 *	0.386190	158.2254	125.6154	At most 1 *	51.73548	46.23142
At most 2 *	0.279720	106.4899	95.75366	At most 2	34.78024	40.07757
At most 3 *	0.231220	71.70967	69.81889	At most 3	27.87272	33.87687
At most 4	0.180727	43.83694	47.85613	At most 4	21.12976	27.58434
At most 5	0.141881	22.70719	29.79707	At most 5	16.21937	21.13162
At most 6	0.058399	6.487819	15.49471	At most 6	6.378383	14.26460
At most 7	0.001032	0.109436	3.841466	At most 7	0.109436	3.841466

Trace test indicates 4 cointegratingeqn(s) at the 0.05 level

Max-eigenvalue test indicates 2 cointegratingeqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

As seen in the Table 4.6, EVIEWS reports the two types of test statistics and we reject the null hypothesis of no cointegrating equation at both test levels since the statistics are greater than the critical value. The trace test suggests 4 cointegrating equations while the maximum eigenvalue suggests two cointegrating equations at the 5% significance level. We realised that both tests differ in their results. As such, we prefer the maximum eigenvalue because it is more realistic.

From the results, we can confirm that though the variables were found non-stationary at their level, a linear combination exist among them and are stationary. These findings conclude that the variables are cointegrated implying that there is the presence of co-movements among the

variables. In other words, the Johansen cointegration test confirms the existence of a stable long run relationship between household debt and the other macroeconomic determinants.

Summing up, in this dissertation based on the maximum eigenvalue, we establish two long run relationships. Philip and Mbanasor (2011) affirmed that the existence of more than one co-integrating vector indicates that the system under examination is stationary in more than one direction and therefore more stable. In conclusion, instead of using the VAR model, it will be suitable for us to use the VECM because cointegration exists among the variables.

Table 4.7 presents the results of the unrestricted cointegrating coefficients that have not yet been normalised.

Table 4.7: Unrestricted cointegrating coefficients

Unrestricted Cointegrating Coefficients (normalized by $b'S11*b=1$)							
LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAY
-2.862475	1.541747	57.64960	-20.74110	-2.061457	-32.33265	52.61786	0.067100
17.52202	-7.316959	-64.73639	-19.44774	-3.087634	67.31131	-64.00675	-0.023860
-1.305349	14.64314	25.01491	-60.02039	3.403007	18.80375	9.519640	0.220202
-11.50763	2.652206	25.72644	-41.40003	-0.097267	4.924148	18.92614	-0.311344
3.043428	5.464028	20.82169	5.041752	-8.221043	-39.17749	26.77644	0.193420
-4.631956	-10.54442	-34.96047	9.278364	-1.035129	38.92941	-28.92409	0.074209
-10.06169	5.216185	-42.46691	6.878452	2.103513	19.48894	-51.72235	-0.259722
6.349797	1.725047	-28.83055	7.778843	0.938124	5.947057	-34.53348	-0.019939

Table 4.7 presents the unrestricted coefficients of each of the cointegrating equations. Therefore, as the Johansen test found two cointegrating equations, we will rely only on the first two equations and identify the one that best suits our theory. Therefore, in Table 4.8 we present the results of the long run cointegrating equations that have been automatically normalized by EVIEWS.

Table 4.8: Automatic normalized cointegrating coefficients

LRHD	LRHPI	LCPI	LRIN	LRIN	LRGDP	LRCON	LRSAY
1.000	0.000	53.051 (13.088)	-29.942 (9.338)	-3.269 (1.284)	-21.878 (12.205)	47.170 (14.060)	0.074 (0.060)
0.000	1.000	135.888 (30.961)	-69.044 (22.091)	-7.406 (3.037)	-61.591 (28.873)	121.707 (33.262)	0.182 (0.144)

The long run cointegrating coefficients are shown in Table 4.8 and their corresponding standard errors are shown in parentheses. These two cointegrating equations are not fully identified unless we imposed some random normalization. The cointegrating vectors have been normalized on household debt because it is considered as the dependent variable in this study and in this way we can be able to express the long run relationship. We were then able to determine the signs and magnitude of the coefficients. In so doing, we can express it as a function of the other remaining variables which will be the explanatory variables. Table 4.9 presents the results about the coefficients of β matrices in terms of the normalized cointegrating coefficients with respect to household debt.

Table 4.9: Normalized cointegrating equations

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAY	Constant
*1.000	-0.515 (0.787) [-0.683]	-16.950 (4.077) [-4.940]	5.625 (3.085) [2.348]	0.546 (0.364) [1.978]	9.850 (3.606) [3.131]	-15.526 (4.124) [-4.460]	-0.0191 (0.018) [-1.299]	70.357
** 1.000	-0.192	26.969	-16.690	-1.147	-10.056	23.8140	0.040	-67.635

* represents the row of the first cointegrating equation

** represents the row of the second cointegrating equation

As seen from Table 4.9, the two equations represent the long run equations. Nevertheless, according to the theory, we expected to have only one cointegrating equation. However, it is worth acknowledging that the first cointegrating equation best reflects the theory though not

all the coefficients bear the normal sign. Therefore, we decided to use the first cointegration equation because it best reflects the theory. To sum up, the first cointegrating equation will be considered in this dissertation as our long run equation.

The economic theory used in this chapter suggests that a finding of cointegration indicates that there may be a long run equilibrium relationship between our variables. As indicated above, the normalized cointegrating coefficients (the cointegrating vector) represent the estimate of the model with all the variables taken to the left hand side. The t-statistics was calculated by taking the ratio of the coefficients to its corresponding standard error. This means that our equation is of the form:

$$LRHD - LRHPI - LCPI + LRIN + LRPR + LRGDP - LRCON + LRS AV = 0$$

This equation therefore constitutes our long-run relationship. In order to interpret our coefficients, we will just need to reverse the signs of our coefficients to get the right signs to check if our estimated coefficients are as anticipated or not. That is taking all the variables to the left hand side except for debt.

Based on economic theory, the estimated long run equation is supposed to take the following signs:

$$LRHD_i = \alpha + \overbrace{\beta_1 LRHPI_i}^+ + \overbrace{\beta_2 LCPI_i}^- + \overbrace{\beta_3 LIN_i}^- + \overbrace{\beta_4 LRPR_i}^- \\ + \overbrace{\beta_5 LRGDP_i}^+ + \overbrace{\beta_6 LRCON_i}^+ + \overbrace{\beta_5 LRS AV_i}^- + \mu_i$$

However, the actual estimated coefficients signs were obtained as follows:

$$LRHD_i = -70.357 + \overbrace{0.515 LRHPI_i}^+ + \overbrace{16.950 LCPI_i}^+ - \overbrace{5.625 LRIN_i}^- - \overbrace{0.546 LRPR_i}^- \\ - \overbrace{9.850 LRGDP_i}^- + \overbrace{15.526 LRCON_i}^+ + \overbrace{0.019 LRS AV_i}^+ + \mu_i$$

From the model, we can say that all the coefficients are statistically significant except for LRHPI, LRPR and LRS AV which have low test statistics. The findings of cointegration

between LRHD, LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON and LRSAB at the 5% significance level suggest the presence of co-movements among the variables, thus indicating long run stationarity. At this stage, the error correction model is appropriate to correct deviation from the long run equilibrium by short run adjustments.

4.7 ESTIMATION OF THE VECTOR ERROR CORRECTION MODEL

The existence of cointegration previously found has been used to derive the VECM. The VECM is estimated to examine the long and short run dynamics between the variables under study. The results of the VECM⁸ incorporating both the long run found in Johansen and the short run model for the first cointegration equation is shown below in Table 4.10.

Table 4.10: VECM results

Variables	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAB
Long run	1.000	-0.515	-16.950	5.625	0.546	9.850	-15.526	-0.0191
Standard error		(0.787)	(4.077)	(3.085)	(0.364)	(3.606)	(4.124)	(0.018)
T- stat		[-0.683]	[-4.940]	[2.348]	[1.978]	[3.131]	[-4.460]	[-1.299]
Variables	ΔLRHD	ΔLRHPI	ΔLCPI	ΔLRIN	ΔLRPR	ΔLRGDP	ΔLRCON	ΔLRSAB
Short run	-0.036	-0.073	0.025	0.003	0.093	-0.047	-0.002	1.455
Standard error	(0.030)	(0.018)	(0.009)	(0.024)	(0.053)	(0.017)	(0.013)	(3.414)
T-stat	[-1.218]	[-4.082]	[2.744]	[0.144]	[1.757]	[-2.789]	[-0.1673]	[0.426]
R-squared: 0.402657								
Adj. R-squared: 0.279069								

⁸The complete VECM with one and two equations can be seen in Appendix A and B

An essential characteristic in cointegration and VECM analysis is testing assumptions (hypotheses) about the cointegrating relations and the adjustment coefficients. By imposing restrictions, we can test the hypotheses that some variables are needed in the long run equation (whether they are significant) and whether some of them can be treated as weakly exogenous. Before proceeding any further, we tested restrictions on the cointegrating vector for the long run exclusion test and the weakly exogenous test.

4.7.1 Long run exclusion test

Though nearly all the variables are statistically significant, for efficient economic interpretation, we decided to test whether a variable belongs to the cointegrating space. The aforementioned test is known as the long run exclusion test. The null hypothesis is that the series is excluded from the cointegrating space. This will be done by equating the corresponding variable to 0. This test is asymptotically distributed as $\chi^2(r)$. Therefore, at a given significance level, we will reject the null hypothesis if the P-value is less than the significance level and we will conclude that the series belong to the long run equation. Table 4.11 presents the results of the long run exclusion test

Table 4.11: Long-Run exclusion test results

Variable	Chi square	Probability	Conclusion
LRHD	40.62087	0.004166	REJECTED
LRHPI	41.10183	0.003615	REJECTED
LCPI	40.72444	0.004041	REJECTED
LRIN	40.86440	0.003877	REJECTED
LRPR	40.53387	0.004274	REJECTED
LRGDP	40.90370	0.003833	REJECTED
LRCON	40.86798	0.003873	REJECTED
LRSV	42.08879	0.002693	REJECTED

The results suggest that all the variables have significant effects at 5% significance level and belong to the cointegrating space and should therefore be included in the model.

4.7.2 Weak exogeneity test

All the variables were found significant and belonging in the model; at this point we also need to ask ourselves if some variables can be treated as weakly exogenous in the system. The most direct route to check this is by imposing restrictions on the adjustment coefficients from the VECM. At this point, we test whether some of the variables under study can be considered as weakly exogenous. The hypothesis of weak exogeneity is expressed by the nullity of some coefficients of α matrix (adjustment coefficients). Just as the previous restriction, this test is also asymptotically distributed as χ^2 . If the p-value is less than the significance level, we reject the null hypothesis and we conclude that the variable is not weakly exogenous to the cointegrating equation. Table 4.12 produces the results of the weak exogeneity tests.

Table 4.12: Weak exogeneity test results

Variable	Chi square	Probability	Conclusion
LRHD	40.73973	0.004023	REJECTED
LRHPI	40.73971	0.004023	REJECTED
LCPI	40.72444	0.004023	REJECTED
LRIN	40.72444	0.004023	REJECTED
LRPR	40.72444	0.004023	REJECTED
LRGDP	40.72444	0.004023	REJECTED
LRCON	40.72444	0.004023	REJECTED
LRSV	40.84252	0.003903	REJECTED

From the results, we conclude that at the significance level of 5%, the variables are not considered as weakly exogenous to the whole system of equations. At this moment, we can

confirm that our previously estimated VECM is plausible. The different tests have shown that all the variables are endogenous and belong to the cointegration space. We can then proceed with the diagnostic test of the estimated VECM.

4.8 DIAGNOSTIC TESTS

As explained in Chapter 3, diagnostic tests are very important especially if we want to know if our model is good and can be used for future analysis. Below we perform several diagnostic tests to check if our estimated model is good.

4.8.1 Autocorrelation test

To confirm whether we have a good model, the residuals from the VECM are supposed to be non-auto correlated. This assumption of non-autocorrelation of error terms is very important because it needs to be satisfied so that we can proceed with the estimation of the dynamic analysis. We conducted the serial correlation Lagrange multiplier test and from Table 4.13 beneath, we can confirm that the residuals do not show any form of autocorrelation⁹.

⁹The portmanteau autocorrelation test also revealed no sign of autocorrelation in the residuals. This is shown in appendix D.

Table 4.13: VEC residual serial correlation LM test results

Null hypothesis: No serial correlation up to lag h

lags	LM-Stat	Probability
1	49.73849	0.9046
2	53.13238	0.8318
3	61.87890	0.5519
4	57.00206	0.7201
5	55.25499	0.7739
6	63.51281	0.4937
7	45.94257	0.9570
8	54.94178	0.7829
9	69.19882	0.3064
10	72.89670	0.2087
11	85.72587	0.0363
12	64.34125	0.4645

Probs from chi-square with 64df.

4.8.2 Heteroskedasticity Test

We can substantiate that the residuals from the VECM do not show any signs of heteroscedasticity at the 5% significance level with a p-value of 0.08.

Table 4.14: VEC Heteroscedasticity test (No cross terms) results

Chi-square	Df	Prob
1375.000	1296	0.0625

4.8.3 Normality Test

The joint Jarque-Bera test of normality shows that the residuals are normality distributed with a p-value of 0.0000. But as alluded in Chapter 3, this is not a very important condition especially if we want to use our estimated model for forecasting. As Stengos and Wu (2006) affirmed, the normality is very sensitive to the number of observations. Table 4.15 presents the results of the normality test of residuals. A detailed description of the results incorporating the skewness and the kurtosis is shown in appendix F.

Table 4.15: Normality test results

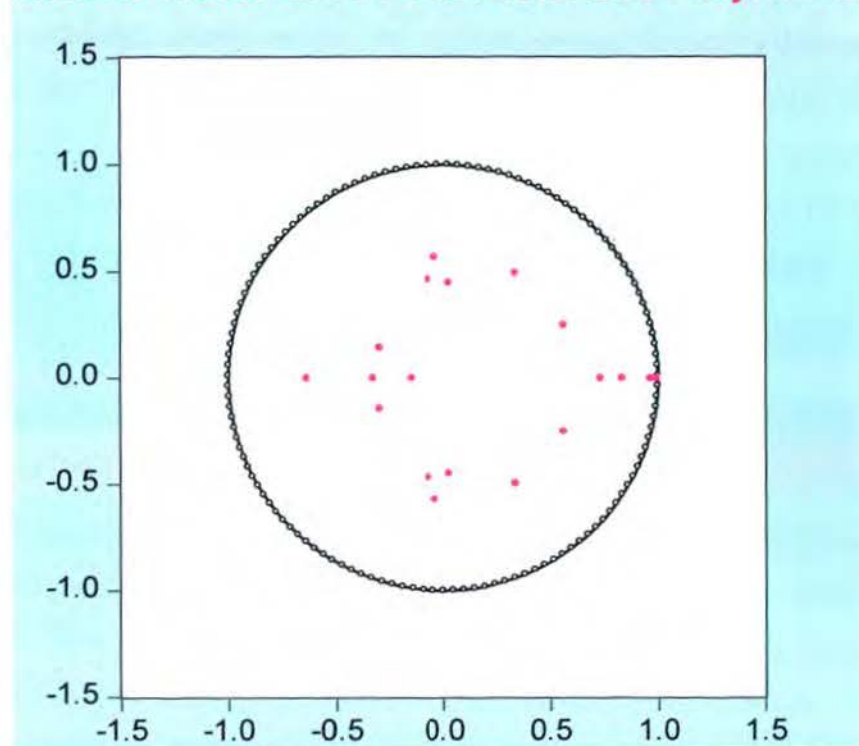
Component	Jarque-Bera	Df	Prob.
1	50.92411	2	0.0000
2	1.115149	2	0.5726
3	2.144356	2	0.3423
4	35.16890	2	0.0000
5	58.92574	2	0.0000
6	1.927570	2	0.3814
7	6.442661	2	0.0399
8	148.2408	2	0.0000
Joint	304.8892	16	0.0000

4.8.4 Stability Test of the VECM

Here, we perform the stability test of the estimated model. Figure 4.4 shows the graphical representation of the stability test. All the inverse roots appear to lie inside the circle, so we conclude that the model is stable and may be properly used for dynamic analysis.

Figure 4.4: Stability test of VECM

Inverse Roots of AR Characteristic Polynomial



With all the diagnostics and stability tests performed, we conclude that the model satisfies the classical conditions (except for normality which is not considered very important). Consequently, we can then proceed with the interpretation of the VECM results and the analysis of the Variance decomposition and the GIRF.

4.9 DISCUSSION OF THE RESULTS

First of all, we notice that the overall system indicates a fair goodness of fit. From the results, the coefficient of determination is 0.40 which confirms a fair goodness of fit. This indicates that approximately 40% of the variation in household debt is explained by the other macroeconomic variables. On the other hand, the remaining 60% can be explained by the omitted variables. Furthermore, we will essentially discuss the VECM results which integrate both the long run cointegration results and the short run ECM.

As shown in Table 4.10, the first part of the VECM results stands for the long run cointegrating equation. As previously mentioned the household debt is the dependent variable and appears to be on the same side of other variables in the cointegrating vector. Therefore,

the opposite signs of the coefficient of the explanatory variables need to be identified in order to get the right interpretation. The outcome reveals the factors that positively affect household debt are LRHPI, LCPI, LRCON and LRSAB. Except for LRHPI and LRSAB, all the other variables are significant but not all of them produced the expected signs as stated by the theory. We first discuss the results of the expected coefficients. However, we then recognize that because our variables have been transformed into natural logarithm, the estimated coefficients will be interpreted as elasticity.

South Africa's long run increase in household debt can be explained by the increase in house prices. The estimated coefficient for the LRHPI is 0.52 which implies that if all the other explanatory variables are kept constant (fixed), then for each percentage increase in LRHPI, LRHD will increase by 0.52% in the long run. This coefficient has the expected sign as confirmed by the theory but unfortunately it turns out to be statistically insignificant with a t-statistics lower than 2. We therefore conclude that a positive linear dependence was found to exist between household debt and house prices but this relationship was found to be statistically insignificant.

Still from the results, we noticed that household debt is also positively influenced by household consumption. The outcome of the results confirms that a 1% increase in LRCON will induce LRHD to change by 15.53%. This finding confirms what was expected from the theory and this tells us that in South Africa, the more households increase their consumption/expenditures, the more they go into debt.

The results reveal that LRHD is positively affected by LCPI and LRSAB which is not what we expected from the theory. The outcome shows that a 1% increase in LCPI increases LRHD by 16.95%. This coefficient is seen to be statistically significant which really confirms the validity of the estimated coefficient. From this conclusion, we can then postulate that the negative relationship between household debt and CPI suggested by the theory does not hold in South Africa for our estimated timeline. Instead, we notice a positive connection between the two variables. Nevertheless, we are cognizant of the fact that there is an insignificant positive correlation between LRHD and LSAV. Though the estimated coefficient was found to be statistically insignificant for the duration of our study, the positive relationship may be representing a tendency for the South African households to still go in for more debt even when their savings records are positive.

Now, having examined the positive factors, we now examine the negative factors and their respective contributions in the changes of household debt. From the outcome, we see that LRHD is negatively affected by LRIN and LRPR. The signs of the coefficients are all as expected and significant except for LRPR. The coefficient of LRIN reveals that a 1% increase in this variable will cause LRHD to decrease by 5.26% and is statistically significant. As expected by the theory, we conclude in South Africa, households borrow more when their income is lowered. On the other hand, the coefficient of LRPR is having the predictable sign but it is insignificant. We then conclude that there is an insignificant negative relationship between household debt and prime rate in South Africa. In other words, this implies that when banks reduce a high interest rate, South African households are encouraged to borrow more because the cost of repayment will be low in comparison to the interest rate. In every economy, higher GDP implies an increase in economic growth which will then lead to higher income and greater consumer confidence. With higher income, banks will be encouraged to lend more money. When GDP increases, households are optimistic about the economy and as such they will be willing to borrow because they are very confident of being able to pay back the debt. The estimated coefficient of LRGDP is significant but does not bear the expected sign. We therefore interpret that a 1% increase in LRGDP will lead to a 9.85% decrease in household debt. This result does not support the hypothesis of the LCH theory and we might conclude that in the case of South Africa over our estimated timeline, the relationship between household debt and GDP in South Africa is negative.

The second part of Table 4.10 presents the results of the short run equation. The result of the error-correction analysis gives some insight into the deviations from the long run relationship described above. The principle behind the VECM is that there often exists a long run equilibrium relationship between economic variables but in the short run however, there may be disequilibrium. Within the ECM, a proportion of the disequilibrium in one period is corrected in the next period. The error correction process is thus a means to reunite short run and long run behavior.

In the Johansen methodology, the residual of the long run equation is expressed in parentheses. This could be defined as the error term which the disequilibrium adjustment process of the error correction model attempts to explain. Hence, the adjustment terms weights the error correction processes and indicate the importance of the past changes of the

explanatory variables in affecting adjustment towards equilibrium. In the short run, the most important part is the analysis of the error correction term. Concerning the coefficients of the other variables, LRHPI, LRGDP and LRCON have the correct negative signs but LRCON appears to be statistically insignificant. However, the remaining variables LCPI, LRIN, LRPR and LRSAV do not have the expected signs.

The coefficient of the error correction term here is -0.036. The sign of the coefficient is negative as expected by the theory but turns out to be statistically insignificant. Though statistically insignificant, the estimated coefficient implies that about 3.6% of the disequilibrium is corrected between each quarter (since we are dealing with quarterly data). That is, from any exogenous shock to the system, it will take 3.6 % each quarter for household debt to get back to equilibrium which is a very slow movement.

4.10 DYNAMIC ANALYSIS OF THE VECM

The dynamic behavior of our estimated model (VECM) can be analyzed using the following two approaches namely the Variance Decomposition and the Generalized Impulse response function (GIRF). Having established earlier that our estimated model was stable, both computations are useful in assessing how shocks to economic variables reverberate through a system.

4.10.1 Variance Decomposition

The main idea behind the variance decomposition is that it provides information about the contributions of each random innovation in affecting the variables in the VECM. The inconvenience with this analysis is that it is very sensitive to ordering. The variance decomposition of household debt¹⁰ over 15 periods (quarters) computed in EVIEWS is shown in Table 4.16.

¹⁰The complete variance decomposition of all the variables is shown in appendix G. We reported only that of household debt because this is our main variables of interest.

Table 4.16: Variance Decomposition of Household Debt

Period	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAY
1	0.0244	100.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0312	88.9231	1.47340	0.1635	4.21206	1.30249	3.45759	0.27222	0.1954
3	0.0368	75.8989	4.26555	0.2345	8.65502	1.19557	5.79585	1.21357	2.7408
4	0.0436	66.9040	7.00878	0.2174	12.3912	0.85684	5.41177	3.14840	4.0614
5	0.0511	58.5400	10.7598	0.3008	15.4388	0.62546	4.93341	4.94581	4.4556
6	0.0589	49.9827	15.2042	0.3274	17.6119	0.50262	4.80538	6.66471	4.9009
7	0.0671	42.6001	19.1532	0.3450	18.9458	0.51819	4.62398	8.38774	5.4256
8	0.0755	36.6034	22.3575	0.3829	19.7186	0.62911	4.47827	10.0032	5.8267
9	0.0838	31.6546	25.0234	0.4330	20.1568	0.77994	4.45520	11.3740	6.1227
10	0.0920	27.5332	27.2724	0.4944	20.3506	0.94494	4.51701	12.5105	6.3767
11	0.1002	24.1212	29.1585	0.5730	20.3863	1.10806	4.60766	13.4602	6.5848
12	0.1082	21.2809	30.7520	0.6677	20.3324	1.25819	4.71301	14.2575	6.7380
13	0.1161	18.8905	32.1136	0.7728	20.2255	1.39216	4.82899	14.9284	6.8478
14	0.1238	16.8643	33.2837	0.8838	20.0860	1.51073	4.94691	15.4970	6.9273
15	0.1314	16.1384	34.2935	0.9978	19.9293	1.6151	5.0601	15.9825	6.9830

Cholesky ordering: LRHD, LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON, LRSAY

From Table 4.16, we will depict the relative significance of each structural shock to the variables in the system. We then report here the variance decomposition of household debt

over a 15 quarters period ahead. In terms of explaining its own shocks, 100 % of household debt variance can be explained by its own innovation in the first period. But as time goes on, it is progressively tumbling to 27.53% in ten quarters. The results further show that household debt shocks up to the 10th quarter are the main drivers of household debt which means that household debt can be forecasted by its own behavior. From the 11th to the 15th quarter, the variation in LRHD is more influenced by LRHPI of which the latter accounts for 34.3% in the variation compared to 16.1% in debt itself.

In the second period, following household debt itself, the above variance decomposition demonstrates the importance of LRIN, LRGDP and LRHPI. LRIN accounts for 4.21% in the variation for household debt while 3.45% and 1.47% is explained by LRGDP and LRHPI respectively. However, as time goes by, the different contributions experienced significant changes. For example, we noticed that from the 10th quarter until the last quarter, the variations in household debt are influenced by LRHPI then by LRIN and finally by LRCON. The contributions of LRHPI in explaining the disparity in household debt increased from 10.75% in the 5th quarter to 34.29% in the last quarter which is quite a significant increase.

On the other hand, LRIN's contribution from 20.35% in the 10th quarter decreased to 19.32% in the last observed quarter. Despite the fact that this contribution experienced a decrease, it still accounts for the second highest contribution in explaining the variation in household debt. Alternatively, from the 8th quarter onwards, the contribution in LRGDP loses value and was replaced by the contribution in LRCON. In the last quarter, LRCON accounts for 15.98% in explaining the deviation in LRHD compared to 5.06% of LRGDP.

Similarly, the contribution of LRSAB to the variance in debt is small but slightly higher than that of LCPI and LRPR. From the 3rd to the 10th quarter, the contribution in innovations of these variables in explaining the variation in household debt experienced significant fluctuations. Afterwards, we observe that the contribution of innovations in the variables grow gradually but little by little with time. At the last quarter, LRSAB accounts for 6.98% in the variation in debt while LRPR and LCPI accounts for just 1.61% and 0.99% correspondingly.

With respect to the aforementioned interpretations, we can conclude that the variation in the household debt in South Africa is mainly explained by the variation in LRHPI, LRIN, LRCON, LRSAP and LRGDP.

4.10.2 Generalized Impulse Response Function (GIRF)

To the best of our knowledge, in the context of this dissertation, the GIRF analysis is the first of its kind. The purpose of doing this is to examine the role played by shocks (crises especially the 2008-2009 financial disaster) in the household debt behaviour in South Africa.

More robust results are expected with the computation of the GIRF compared to the results from the IRF because GIRF is invariant to the ordering of variables. The GIRF over 15 quarters for our VECM estimation is shown in Figure 4.5 and 4.6. In interpreting the results of the computation of the GIRF, more emphasis is shown for the response of debt to shocks in the other variables and the response of other variables to the one-off shock of household debt¹¹.

¹¹Due to the fact we have many variables, the whole system of the GIRF contain too many graphs. Therefore, we reported only the most important ones. The complete GIRF is shown in Appendix H.

Figure 4.5: Response to Generalized one S.D. Innovation

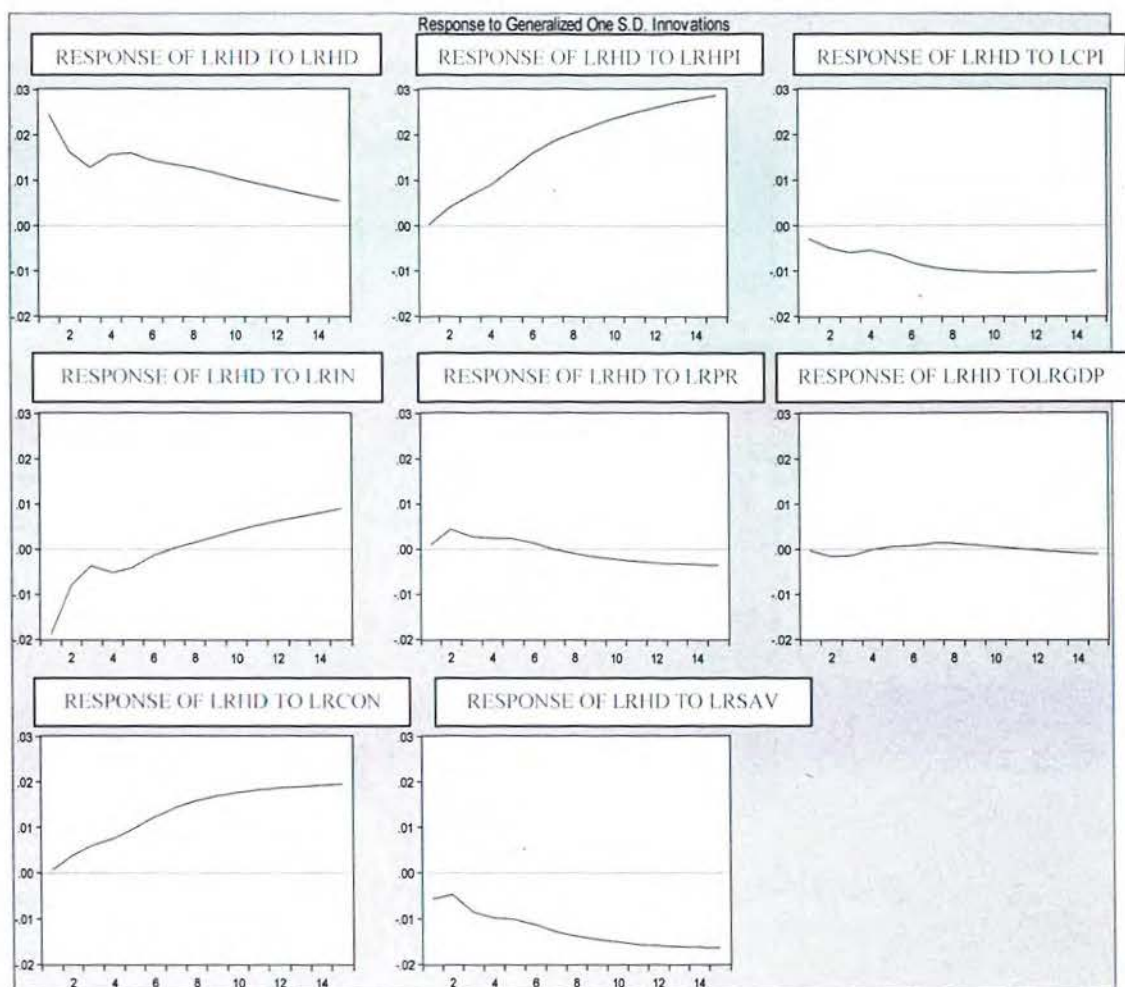
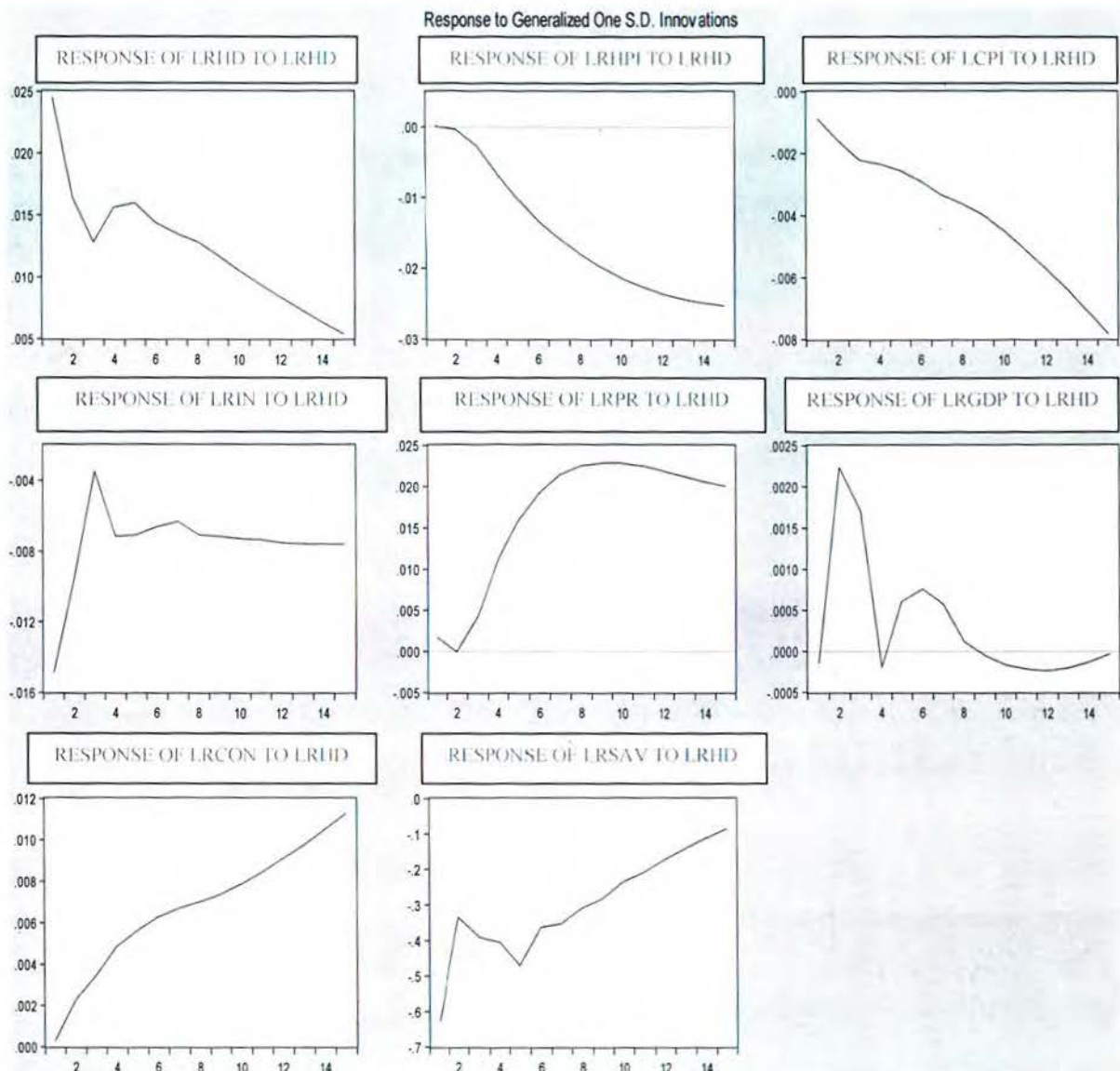


Figure 4.6: Response to Generalized One S.D. Innovations



From Figure 4.5, the response of debt to house price shock and consumption shock remained significant in all the quarters and keeps on trending overtime. This can be significantly justified taking into account the recent financial crisis of 2007/2008 with the house price bubble that began in the United States of America. This positive response is also in accordance with the theory. We can rationalize that a positive standard deviation shock to LRHPI will cause household debt to increase in South Africa.

From the results, we observe that the response of LRHD to shocks from LCPI and LRSAY are identical. A positive shock on these variables will cause household debt to respond

negatively. These responses are also in line with what we expected from the theory. We therefore postulate that a positive financial shock on the consumer price index and household savings will have a negative impact on household debt in South Africa.

We noticed that the response of debt to shocks from income, prime rate and GDP reveal fluctuating behavior during the observed period. With regard to income shock, the response is first negative. However, after a certain period, it keeps on increasing up to the 7th quarter and then it becomes positive up to the last observed period. Also, the shock from LRPR is positive during the first 7 quarters and negative from the 8th quarter to the final period. We observe from Figure 4.5 that the response of household debt to GDP shock shows a nearly insignificant response. It is initially negative till the 4th quarter and then becomes positive from the 4th to 9th quarter. We also noticed that from the 10th to 12th quarters, it becomes insignificant and from the 13th to 15th quarter responds negatively.

From the above discussions, we can deduce that GIRF results validate that shocks from LRHPI and LRCON will definitely have a positive effect on household debt in South Africa while shocks from LCPI and LRSAB will negatively influence it. Moreover, the response of household debt will show fluctuating behaviors to shocks from LRIN, LRPR and LRGDP.

Now we consider the interpretation of the response of other variables to a one generalized standard deviation innovations. Figure 4.6 shows that all the variables appear to respond significantly from a shock to debt.

The outcome of the GIRF reveals that an adjustment in the level of household debt will cause LRHPI, LCPI, LRIN and LRSAB to respond negatively. The response of LCPI, LRIN, and LRSAB appear to be negative from a shock in household debt. However, the response of LRHPI is different from the responses of the other variables. The LRHPI response is insignificant at the beginning of the three quarters and later on changes into a negative response till the last observed period. We can then conclude that a shock on household debt will lead to a negative response in LRHPI, LCPI, LRIN and LRSAB. Except for LRHPI, these results confirm the theory that rising household debt comes from a decrease in household income, CPI and savings.

Moreover, the response of LRPR and LRCON to shocks from LRHD appears to be positive. We notice from Figure 4.6 that a positive shock on household debt will cause LRCON to

increase with this positive response being recognized and reiterated in the theory. The response of LRPR appears to be positive in the 1st quarter but shows an insignificant effect in the middle of the 1st quarter and then becomes positive from the 2nd quarter onwards. The positive response of prime rate to a shock from household debt is not what we expected from LCH theory. On the other hand, the response of LRGDP to a positive shock in household debt shows considerable fluctuating behaviour from the 1st to last observe period.

With the above explanations, we analyzed how household debt will respond from a shock in other variables and vice versa.

As we initially assumed, unemployment is perceived as a significant influence in affecting the increasing level of household debt. As a result, we see the need of conducting a separate analysis to determine if there exist a possible connection between household debt and unemployment in South Africa. Practically, unemployment means lower income for households. So, it will be necessary and significant for this study to investigate this connection between the two variables by the means of an econometric analysis using annual data.

4.11 RELATIONSHIP BETWEEN HOUSEHOLD DEBT AND UNEMPLOYMENT USING ANNUAL DATA

In this section, using annual data from the period 1980 to 2010, we test if there exists a long run relationship between household debt and unemployment using the two step Engle granger method. The model function we want to test is as follows:

$$LHD = \beta_0 - \beta_1 LUN + \varepsilon_t \quad (4.1)$$

Where LHD stands for the natural log of household debt

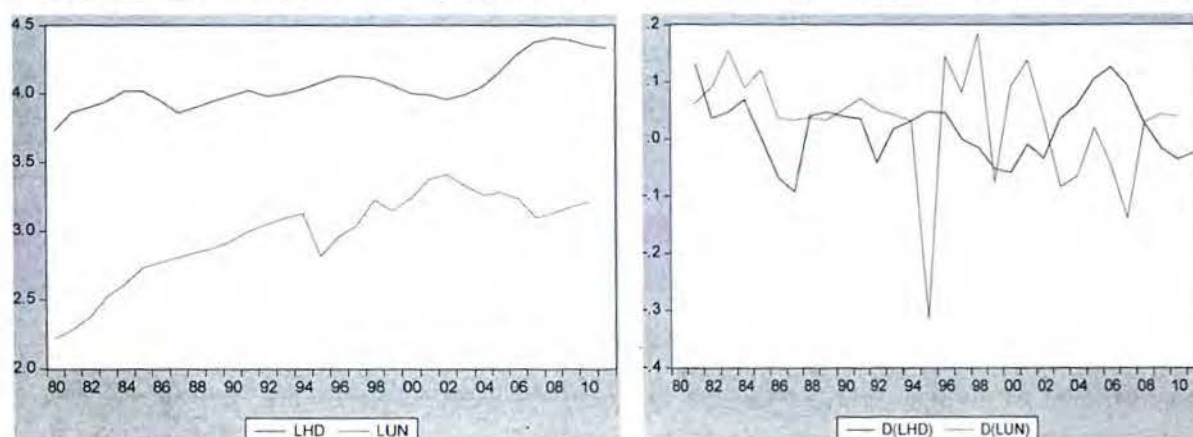
LUN stands for the natural log of unemployment

The theory supports that there exists a negative relationship between household debt and unemployment. So, the purpose of this test is to examine whether this theory holds in the case of South Africa.

4.11.1 The stationarity test

The first step of this analysis is to check if the variables contain a unit root. But before, we do that, we represent a visual inspection of the variables at level and at first difference in Figure 4.7. We see that the variables are trending and they even appear to move together in time. The figure further confirms that the two series are non-stationary and therefore contain a unit root. At their difference, LHD seems stationary but concerning LUN it does not totally show a stationary process. This doubt will be confirmed by the use of a unit root test.

Figure 4.7: Graphical Inspections of the Series at Level and First Difference



As the graphical inspection reveals the presence of a unit root, we will confirm this by the means of a unit root test. The first step of this analysis is to test if the data contains a unit root. We perform unit root tests on the variables using the ADF and the PP test. The results in Table 4.17 reveal that all the variables are $I(1)$.

Table 4.17: ADF and PP test results

Test	Model	Variable	Level of test	Test statistics (lags)	Critical value (5%)	Critical value (10%)	Conclusion
ADF test	Constant	LHD	Level	-1.408(1)	-2.963	-2.621	
			1 st diff	-3.217(5)	-2.986	-2.63	I(1)**
	Constant	LUN	Level	-2.639(0)	-2.963	-2.621	
			1 st diff	-5.07(0)	-2.986	-2.63	I(1)**
PP test	Constant	LHD	Level	-1.415(2)	-2.963	-2.621	
			1 st diff	-3.038(4)	-2.986	-2.63	I(1)**
	Constant	LUN	Level	-4.351(16)	-2.963	-2.621	I(0)**
			1 st diff	-5.067(4)	-2.986	-2.63	

** denotes significance level at 10%

From Table 4.17, both tests confirm that LHD and LUN are stationary after their first difference except for LUN which appears stationary at level using the PP test. But we will proceed considering that both variables are I (1) as the ADF test confirmed. Our next step is to perform the OLS regression and test for cointegration in the residuals to see if there is existence of any long run relationship between the two variables or if the regression is spurious.

4.11.2 Testing for cointegration

The estimation of the long run relationship using OLS between LHD and LUN is presented below:

Table 4.18: Long run equation

Dependent Variable: LHD

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LUN	0.283412	0.080898	3.503338	0.0015
C	3.213138	0.242133	13.27016	0.0000
R-squared	0.297368	Mean dependent var	4.056825	
Adjusted R-squared	0.273139	S.D. dependent var	0.164180	
S.E. of regression	0.139973	Akaike info criterion	-1.032388	
Sum squared resid	0.568184	Schwarz criterion	-0.939872	
Log likelihood	18.00201	Hannan-Quinn criter.	-1.002230	
F-statistic	12.27337	Durbin-Watson stat	0.238479	
Prob(F-statistic)	0.001511			

From the results, we notice that the coefficient of LUN is 0.28 and is statistically significant with a t-value of 3.50. This therefore means that a positive relationship exists between LHD and LUN which is not in accordance with our theory. However, we recognize that this relationship can only be significant if we find cointegration to exist between the variables. If cointegration is found among the variables, we can therefore conclude that the estimated regression is not spurious. Therefore, in order to check if this regression is not a fake relationship, we have to test for cointegration by testing if the residuals of the series are stationary. Therefore, our next step here involves testing for stationarity on the residuals of the series to confirm if the variables move together with time or not.

The results of the stationarity test performed on the residuals using the ADF and PP test is presented below in Tables 4.19 and 4.20 respectively.

Table 4.19: ADF test results on residuals

Null Hypothesis: RESID01 has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=7)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.606383	0.1032
Test critical values: 1% level	-3.679322	
5% level	-2.967767	
10% level	-2.622989	

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

Table 4.20: PP test results on residuals

Null Hypothesis: RESID01 has a unit root

Exogenous: Constant

Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-1.528038	0.5060
Test critical values: 1% level	-3.670170	
5% level	-2.963972	
10% level	-2.621007	

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

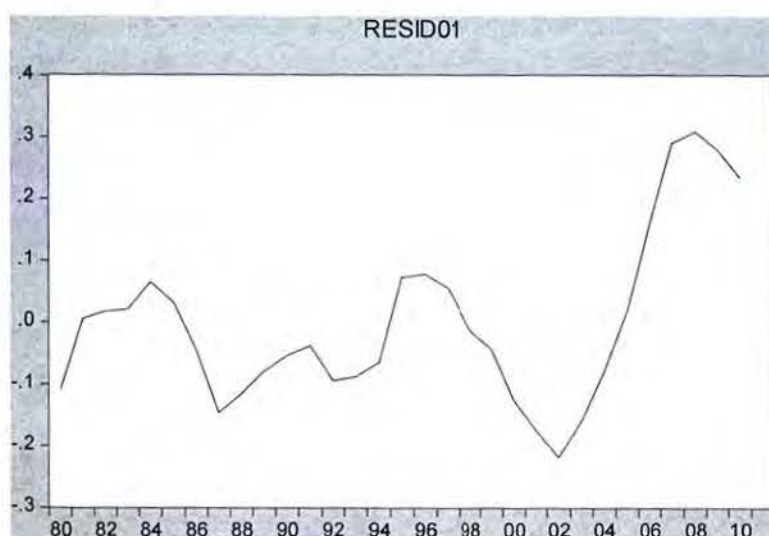
Cointegration will exist among the variables if the error terms of the estimated regression are found stationary at their level. In other words the residuals have to be $I(0)$. The results of both tests confirm that the residuals of the regression are not stationary at their level. This is seen with the t-statistics (ADF and PP) value greater than the critical values at all significance levels. Nevertheless, it is important to mention that according to the literature, the critical values of the ADF and PP test do hold when residuals are being tested (see MacKinnon, 1990). The correct critical values for the Engle granger test based on MacKinnon, 1990 is provided below in Table 4.20 for the model of a constant only.

Table 4.21: Engle granger critical values

1%	-3.89644
5%	-3.33613
10%	-3.04445

With the right critical values we still realise that the residuals of the OLS regression are still non-stationary with the corresponding t-statistics values greater than the critical values at all critical values. We therefore conclude that the residuals are non-stationary which violates the assumption of cointegration. The non-stationarity of the residuals can be confirmed in Figure 4.8.

Figure 4.8: Graph of residuals



The plotted residual graph confirms that the residuals of the regression are not $I(0)$, therefore non-stationary. As we formerly stated, the regression performed above could be considered non spurious only if the variables were cointegrated. Cointegration could be seen between the variables if the residuals of the equation were $I(0)$. Unfortunately, the errors were found non-stationary confirming that the series are not cointegrated. The failure to confirm that LHD and LUN are not cointegrated means that there is no long run connexion that exists between them. In other words, this implies that the equation performed in Table 4.17 is spurious and cannot be interpreted as an equilibrium relationship.

This then allow us to conclude that, using the Engle granger methodology, we did not find any connection that exists between household debt and unemployment in South Africa for the period 1980-2010.

This chapter has presented the results of all the tests and we were able to examine the main reasons why household debt levels increase at an astonishing rate in South Africa. Also, we examine how household debt and its influences responded when a given exogenous shock hits the whole system. Moreover, considering the fact that unemployment played a major role in the increase in household debt according to the theory, we presented the results of a separate analysis to investigate if this relationship holds in South Africa. Consequently, the following chapter will describe the implications and, conclusions of the above results. Finally recommendations for future research are suggested.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

“Economic depression cannot be cured by legislative action or executive pronouncement. Economic wounds must be healed by the action of the cells of the economic body - the producers and consumers themselves.”

Herbert Hoover

5.1. INTRODUCTION

5.2. CONCLUSIONS

5.3. RECOMMENDATIONS

5.4. FUTURE RESEARCH

5.1 INTRODUCTION

The essential purpose of this dissertation was to consider how the level of household debt in South Africa was affected “before”, “during” and “after” the 2008-2009 financial crisis. Another major aim of this thesis was to examine the main causes of increasing household debt in South Africa. Specifically, we examine the long run and short run relationship between household debt and seven macroeconomic variables over the timeline 1985 Q1 to 2012 Q1. These macroeconomic variables are real house price index, consumer price index, real income, real prime rate, real gross domestic product, real household consumption expenditures and real savings. The chosen timeline has enhanced our research in the sense that it covers the period before, during and after the 2008-2009 financial crisis. Also, an extra significant goal was to analyze if there exist any substantial connection between household borrowing and unemployment in South Africa over the period 1980 to 2010. Finally, the interesting aspect of this dissertation which constitutes the main aim was to access the effect of the recent financial crisis (2008-2009) on household debt in South Africa.

5.2 CONCLUSION OF RESULTS

The selection of the variables to be investigated was based on the theoretical and empirical research framework. The chosen variables were commonly used in the literature to scrutinize the main impacts of increasing household borrowing. The objectives of this dissertation were fulfilled with the aid of an extensive econometric analysis. Precisely, econometric techniques such as the Johansen cointegration test, Engle granger cointegration test, VECM analysis, Variance Decomposition analysis and the GIRFs were used.

We conclude that the 2008-2009 crisis affected the level of household debt to a lesser extent than most other countries in the world (especially the US and European countries). We could also possibly associate the decrease in the level of household debt during the period of the crisis to the effects of the implementation of the NCA in South Africa.

Moreover, graphical inspection of household debt suggests that the 2007 SMC which led to the 2008-2009 financial crisis affected the level of household debt in South Africa to a lesser extent. Before the period of the crisis, household debt levels were very high and continued to increase rapidly. During the period of the crisis, we notice that the level of household borrowing kept on increasing and experienced a slight decrease but still remained very high. The implementation of the NCA in South Africa in 2007 suggests that the subsequent decrease in household debt in that period was not only caused by the SMC but also by the application of the aforementioned act.

The Johansen cointegration analysis confirmed that the selected macroeconomic variables all move together in the long run. To have a meaningful relationship, the cointegrating vector was normalized on household debt. We concluded that the long run increase in household debt can be attributed significantly to LCPI, LRIN, LRGDP and LRCON. We also came to the conclusion that not all the variables had the expected signs as the theory suggested.

The results of the cointegration test demonstrated that rising house prices and household savings act as a cause of growing household debt in the long run. The coefficients of these two variables were found positive but insignificant. The coefficient of LRHPI was as expected but that was not the case for LRSAP. We then conclude that although LRHPI and

LRSV were found to be statistically insignificant, we can still say there is a positive connection between these variables and household debt in South Africa.

Moreover, we found that household borrowing is positively determined by CPI and LRCON. All these variables were statistically significant and their signs were as expected except for CPI. According to the theory, a low inflation rate will contribute to rising household debt levels but this situation was not found in the case of South Africa. This implies that this theoretical link does not hold in the case of South Africa and we therefore postulate that a higher inflationary rate will lead to higher debt levels. Likewise, the outcome of the analysis also confirms that higher domestic consumption will lead to increased level of debt in the household sector in the South African economy.

The Johansen results also reveal that household debt levels are negatively affected by LRIN and LRPR. The signs of these coefficients were as expected according to the theory but only LRIN is statistically significant. The significant effect of LRIN on household debt implies that household debt levels are increased because households do not have enough money in their pockets to meet their daily expenses. As a result they are obliged to borrow. We therefore conclude that household debt and income significantly move together in an opposite direction in South Africa. Despite the fact that the coefficient of LRPR was found to be insignificant, we concluded that this variable negatively affects household debt in the long run.

The results of our econometric analysis reveal that there is a negative connection between household debt and GDP over the estimated timeline. The theory, however, suggests that higher GDP which implies higher economic growth will encourage households to apply for more debt. Our results confirm that this hypothesis does not hold in South Africa over our timeline.

In the short run, the VECM results revealed that the variables LRHPI, LRGDP and LRCON bear the correct signs for the error terms but LRCON appear to be statistically insignificant. The remaining variables, LCPI, LRIN, LRPR, LRSVs, do not have the correct signs as expected.

However, the most important part of this section is to analyze the speed at which previous deviations from equilibrium are corrected. This can be analyzed through the coefficient of the error correction term. This coefficient had the expected sign (negative) and significant. In conclusion, we confirm that in the short run, about 3.6% of the disequilibrium is corrected each quarter for the whole system to be reestablished back to equilibrium.

Again, out of the main data set, the connection between household debt and unemployment was investigated using the Engle granger cointegration technique. The result of this approach revealed that there was no cointegration that exists between the two variables on our chosen time line. Based on the results of no cointegration, we then come to the conclusion that there is no significant long run relationship between household debt and unemployment in South Africa and hence no short run relationship.

To access the impact of the shock on household debt, we made use of the tools of dynamic analysis such as Variance Decomposition and GIRF. The results of the variance decomposition show the great importance of LRHPI, LRIN, LRCON and LRSAB in affecting household debt. On the other hand, the GIRF reveals the dynamic process of the response of household debt to various shocks. Furthermore, the GIRF results established the significant positive response of household debt to a shock from real house price index and real consumption. The response of debt to shocks from LCPI and LRSAB is negative and this outcome is confirmed by the theory. However, the response of debt shows fluctuating behaviours to shocks from LRIN, LRPR and LRGDP over the estimated period.

In conclusion, our econometric investigation highlighted the main causes of the high levels of household debt in South Africa both in the short and long run. The GIRFs confirm that shocks like the financial crisis incident of 2008/2009 had a significant impact on real house price index, consumer price index, real household consumption and real savings. The remaining variables, LRIN, LRPR, and LRGDP, all had significant effects on the response of household debt but with inconsistent disparities. Finally, based on the stability, validity and reliability of our model, we recommend its use to facilitate policy analysis and decision making regarding household debt levels in South Africa.

Based on the results of this study, we propose the following policy suggestions for SA's government and financial institutions in order to manage SA's household debt.

5.3 RECOMMENDATIONS

The results of the cointegration test revealed that income contributes to the increasing character of household debt in the long run. Income appeared to be inversely related to debt. This relationship supports the idea that low income leads to higher debt. The low income rate in South Africa could be due to a consequence of high level of unemployment rate in the country. Though this dissertation could not find a plausible relationship between debt and unemployment, we believe that unemployment acts as a major cause of low income in the household sector. Consequently, we suggested that the government should remedy the problem of unemployment by the creation of new jobs as it represents one of the main macroeconomic challenges in South Africa. By doing so, households will be found with more money in their pockets and will in turn make less debt. We therefore postulate that debt in the household sector can be lowered if more jobs are created in the economy which will drive more income into the household sector.

Higher consumption was found to contribute significantly in the increase in household debt levels in all the different analyses conducted in this dissertation. The theory supports the hypothesis that higher household consumption expenditures lead to increased household debt levels. We conclude that if households are faced with lower income in their pockets, in order to meet all their expenses, they must go in for more debt. Therefore, appropriate attention should be engaged on how households spend their money. We recommend that households should spend carefully by meeting their basic needs so that in return their debt will decrease.

Though house price index and prime rate were found to be insignificant but having the correct sign, we believe that it plays a great role in affecting the development of household debt in South Africa. The significant role played by these two variables was also seen in the GIRF analysis. Therefore, we propose closer supervision of the housing market because, housing debt represents the main component of household debt in South Africa. In particular, the government should be very strict when new homes are issued to households. Also, we recommend that in issuing new homes to households, their credit conditions have to be

examined very closely and houses should however be given to households with good credit conditions. If this is done, this will boost not only the money lenders to be more professional in the giving out of loans but also households will be more responsible when they go in for debt and in return will develop an attitude of keeping good credit conditions.

On the other hand, interest rates are official instruments used by every country to control the amount of credit extended to the private sector and therefore should be used with big concern. The outcome of our results proposes that prime rate negatively affects household debt even though it was found to be statistically insignificant. The GIRF analysis shows that positive external shocks on this variable will cause household debt to decrease. These results are all aligned with the theory. Based on these results, care should be taken to avoid large economic shocks since shocks on this variable can have a significant influence on other macroeconomic variables and household debt in particular. Dynan (2012) quoted this *“Even households with positive net worth often choose to hold some debt. This behaviour arises in part because of the convenience of using credit cards, but more significantly when a household wants to own a home and its desired housing services correspond to a property with value exceeding the household’s wealth. In this case, the household not only has a motivation for borrowing but also can use the home as collateral in order to create an ability to borrow that would not otherwise exist”*. With this statement, we believe that the dismissal of credit card debt could contribute to a reduction of a large amount of debt in the household sector in South Africa.

This study has contributed a lot to the understanding of South Africa’s household debt but the lack of quarterly available unemployment data was a limitation. Even though a separate analysis was conducted to find any existing relationship with household debt, we believe that this study will have been more significant if this variable was included in the main data set. A number of reasons could be enumerated why a significant relationship was not found between these two variables. Firstly, increasing household debt levels is found to be influenced by many factors. Therefore, conducting an analysis using only one of the factors will certainly give us biased results. Also, annual data does not actually give us detailed insight about the fluctuations of the variables under study compared to quarterly data. This also comes as a serious limitation.

Consequently, we acknowledge if quarterly unemployment data was available, we could certainly find a significant relationship between household debt and this variable if it was included in the main data set.

5.4 FUTURE RESEARCH

Because South Africa lacks quarterly unemployment data, for future investigations, we recommend that this variable should be analysed together with other variables in a VECM using annual data. This analysis will be very significant because we will then capture the role that unemployment has to play in affecting household debt levels in South Africa.

For future analysis, we also suggest the inclusion of vehicle sales data as a variable in the model. This will bring more significance to the study because it would supplement the house prices data used. Also, this will be significant because it has been observed that households increase their debt to finance the consumption of their fixed assets such as houses and cars.

Also, we will like to encourage more national and international studies using this type of econometric approach for future research to facilitate researchers in the interpretation and comparison of such complex economic relationships.

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APPENDICES

APPENDIX A: Johansen Cointegration test

Date: 12/18/12 Time: 15:20

Sample (adjusted): 1985Q4 2012Q1

Included observations: 106 after adjustments

Trend assumption: Linear deterministic trend

Series: LRHD LRHPI LCPI LRIN LRPR LRGDP

LRCON LRSAV

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 *	0.477041	226.9401	159.5297	0.0000
At most 1 *	0.386190	158.2254	125.6154	0.0001
At most 2 *	0.279720	106.4899	95.75366	0.0074
At most 3 *	0.231220	71.70967	69.81889	0.0351
At most 4	0.180727	43.83694	47.85613	0.1134
At most 5	0.141881	22.70719	29.79707	0.2607
At most 6	0.058399	6.487819	15.49471	0.6378
At most 7	0.001032	0.109436	3.841466	0.7408

Trace test indicates 4 cointegratingeqn(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 *	0.477041	68.71474	52.36261	0.0005
At most 1 *	0.386190	51.73548	46.23142	0.0117
At most 2	0.279720	34.78024	40.07757	0.1752
At most 3	0.231220	27.87272	33.87687	0.2194
At most 4	0.180727	21.12976	27.58434	0.2684
At most 5	0.141881	16.21937	21.13162	0.2123
At most 6	0.058399	6.378383	14.26460	0.5652
At most 7	0.001032	0.109436	3.841466	0.7408

Max-eigenvalue test indicates 2 cointegratingeqn(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=l):

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAV
-2.862475	1.541747	57.64960	-20.74110	-2.061457	-32.33265	52.61786	0.067100
17.52202	-7.316959	-64.73639	-19.44774	-3.087634	67.31131	-64.00675	-0.023860

-1.305349	14.64314	25.01491	-60.02039	3.403007	18.80375	9.519640	0.220202
-11.50763	2.652206	25.72644	-41.40003	-0.097267	4.924148	18.92614	-0.311344
3.043428	5.464028	20.82169	5.041752	-8.221043	-39.17749	26.77644	0.193420
-4.631956	-10.54442	-34.96047	9.278364	-1.035129	38.92941	-28.92409	0.074209
-10.06169	5.216185	-42.46691	6.878452	2.103513	19.48894	-51.72235	-0.259722
6.349797	1.725047	-28.83055	7.778843	0.938124	5.947057	-34.53348	-0.019939

Unrestricted Adjustment Coefficients (alpha):

D(LRHD)	-0.002197	-0.003535	-0.002750	-0.005112	0.002454	-0.001931	0.003781	0.000151
D(LRHPI)	0.005814	-0.004531	0.000388	0.000823	0.000575	0.003577	0.000793	1.86E-05
D(LCPI)	-0.004848	0.000819	-0.001258	3.61E-05	-0.000846	4.90E-05	-0.000517	6.41E-05
D(LRIN)	0.004523	0.001413	0.004473	0.005891	0.000954	0.000503	-0.001711	-4.22E-06
D(LRPR)	0.007745	0.009580	-0.013611	0.001873	0.003152	-0.000518	-0.002183	0.000732
D(LRGDP)	0.003193	-0.003037	-0.001190	0.002123	0.003611	-0.000489	-0.000103	-0.000178
D(LRCON)	0.004552	0.000968	0.001383	0.000551	0.002396	0.000809	0.000670	-0.000114
D(LRSAV)	0.056406	0.133088	-0.363268	0.939073	-0.479841	-0.214461	0.155947	-0.006883

1 Cointegrating Equation(s): Log likelihood 1999.201

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSV
1.000000	-0.538606	-20.13977	7.245861	0.720166	11.29535	-18.38194	-0.023441
	(0.78786)	(4.07705)	(3.08554)	(0.36405)	(3.60659)	(4.12142)	(0.01804)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	0.006288
	(0.00685)
D(LRHPI)	-0.016642
	(0.00428)
D(LCPI)	0.013878
	(0.00206)
D(LRIN)	-0.012948
	(0.00534)
D(LRPR)	-0.022169
	(0.01235)
D(LRGDP)	-0.009141
	(0.00391)
D(LRCON)	-0.013031
	(0.00289)
D(LRSAV)	-0.161461
	(0.77169)

2 Cointegrating Equation(s): Log likelihood 2025.069

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSV
1.000000	0.000000	53.05064	-29.94201	-3.269232	-21.87836	47.17047	0.074825
		(13.0881)	(9.33859)	(1.28414)	(12.2053)	(14.0608)	(0.06096)
0.000000	1.000000	135.8885	-69.04460	-7.406890	-61.59174	121.7074	0.182445
		(30.9618)	(22.0918)	(3.03784)	(28.8735)	(33.2629)	(0.14421)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	-0.055649	0.022477
	(0.04196)	(0.01767)
D(LRHPI)	-0.096031	0.042115
	(0.02513)	(0.01058)
D(LCPI)	0.028224	-0.013466
	(0.01270)	(0.00535)
D(LRIN)	0.011812	-0.003365
	(0.03301)	(0.01390)
D(LRPR)	0.145692	-0.058156
	(0.07443)	(0.03135)
D(LRGDP)	-0.062348	0.027142
	(0.02356)	(0.00992)
D(LRCON)	0.003925	-6.20E-05
	(0.01785)	(0.00752)
D(LRSAV)	2.170511	-0.886837
	(4.77969)	(2.01308)

3 Cointegrating Equation(s): Log likelihood 2042.459

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSV
1.000000	0.000000	0.000000	-4.420292	-0.257991	3.089687	-0.717083	0.008953
			(0.85868)	(0.11176)	(0.76290)	(0.17897)	(0.00500)
0.000000	1.000000	0.000000	-3.671084	0.306364	2.363566	-0.955858	0.013715
			(0.84737)	(0.11029)	(0.75285)	(0.17662)	(0.00494)
0.000000	0.000000	1.000000	-0.481082	-0.056762	-0.470645	0.902676	0.001242
			(0.16255)	(0.02116)	(0.14442)	(0.03388)	(0.00095)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	-0.052059	-0.017788	0.033402
	(0.04175)	(0.03856)	(0.21158)
D(LRHPI)	-0.096538	0.047801	0.638194
	(0.02518)	(0.02326)	(0.12764)
D(LCPI)	0.029866	-0.031882	-0.363966
	(0.01251)	(0.01155)	(0.06340)
D(LRIN)	0.005973	0.062136	0.281195
	(0.03199)	(0.02955)	(0.16212)
D(LRPR)	0.163458	-0.257458	-0.514168
	(0.07002)	(0.06467)	(0.35486)
D(LRGDP)	-0.060795	0.009723	0.350921
	(0.02352)	(0.02172)	(0.11918)
D(LRCON)	0.002119	0.020193	0.234399
	(0.01770)	(0.01635)	(0.08972)
D(LRSAV)	2.644702	-6.206213	-14.45096
	(4.74275)	(4.38035)	(24.0364)

4 Cointegrating Equation(s): Log likelihood 2056.395

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSV
1.000000	0.000000	0.000000	0.000000	-0.105612	0.171237	-0.086162	0.026383
				(0.12151)	(0.26305)	(0.13896)	(0.00540)
0.000000	1.000000	0.000000	0.000000	0.432916	-0.060227	-0.431874	0.028191
				(0.14241)	(0.30830)	(0.16287)	(0.00632)
0.000000	0.000000	1.000000	0.000000	-0.040177	-0.788275	0.971342	0.003139

				(0.02205)	(0.04774)	(0.02522)	(0.00098)
0.000000	0.000000	0.000000	1.000000	0.034473	-0.660239	0.142733	0.003943
				(0.02702)	(0.05850)	(0.03090)	(0.00120)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	0.006767	-0.031346	-0.098110	0.490984
	(0.04835)	(0.03799)	(0.21399)	(0.17850)
D(LRHPI)	-0.106013	0.049985	0.659378	-0.089870
	(0.02993)	(0.02352)	(0.13247)	(0.11050)
D(LCPI)	0.029450	-0.031786	-0.363037	0.158626
	(0.01490)	(0.01170)	(0.06593)	(0.05500)
D(LRIN)	-0.061818	0.077760	0.432747	-0.633668
	(0.03569)	(0.02804)	(0.15796)	(0.13176)
D(LRPR)	0.141899	-0.252489	-0.465970	0.392411
	(0.08327)	(0.06542)	(0.36853)	(0.30742)
D(LRGDP)	-0.085226	0.015354	0.405537	-0.023673
	(0.02759)	(0.02168)	(0.12210)	(0.10186)
D(LRCON)	-0.004223	0.021655	0.248578	-0.219082
	(0.02104)	(0.01653)	(0.09313)	(0.07769)
D(LRSAV)	-8.161799	-3.715599	9.708047	-20.83237
	(5.23353)	(4.11183)	(23.1629)	(19.3220)

5 Cointegrating Equation(s): Log likelihood 2066.960

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAV
1.000000	0.000000	0.000000	0.000000	0.000000	0.387113	-0.179142	0.027771
					(0.20554)	(0.12516)	(0.00604)
0.000000	1.000000	0.000000	0.000000	0.000000	-0.945127	-0.050738	0.022504
					(0.20269)	(0.12343)	(0.00595)
0.000000	0.000000	1.000000	0.000000	0.000000	-0.706150	0.935970	0.003667
					(0.04075)	(0.02481)	(0.00120)
0.000000	0.000000	0.000000	1.000000	0.000000	-0.730703	0.173082	0.003490
					(0.03707)	(0.02257)	(0.00109)
0.000000	0.000000	0.000000	0.000000	1.000000	2.044045	-0.880393	0.013137
					(0.37025)	(0.22546)	(0.01088)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	0.014234	-0.017940	-0.047021	0.503355	-0.013589
	(0.04852)	(0.03971)	(0.21775)	(0.17769)	(0.02185)
D(LRHPI)	-0.104262	0.053129	0.671360	-0.086969	-0.001485
	(0.03021)	(0.02473)	(0.13556)	(0.11063)	(0.01360)
D(LCPI)	0.026875	-0.036409	-0.380654	0.154361	0.010139
	(0.01492)	(0.01222)	(0.06697)	(0.05465)	(0.00672)
D(LRIN)	-0.058915	0.082972	0.452608	-0.628859	-0.006881
	(0.03599)	(0.02946)	(0.16151)	(0.13180)	(0.01620)
D(LRPR)	0.151491	-0.235268	-0.400348	0.408300	-0.117953
	(0.08381)	(0.06860)	(0.37612)	(0.30693)	(0.03773)
D(LRGDP)	-0.074237	0.035083	0.480718	-0.005469	-0.031146
	(0.02662)	(0.02179)	(0.11948)	(0.09750)	(0.01199)
D(LRCON)	0.003068	0.034745	0.298458	-0.207004	-0.027413
	(0.02054)	(0.01681)	(0.09219)	(0.07523)	(0.00925)
D(LRSAV)	-9.622161	-6.337464	-0.283057	-23.25161	2.090045
	(5.17248)	(4.23358)	(23.2117)	(18.9419)	(2.32875)

6 Cointegrating Log 2075.070

Equation(s): likelihood

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSVA
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-0.176965 (0.08474)	0.013556 (0.00236)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	-0.056052 (0.19109)	0.057210 (0.00531)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.932000 (0.10940)	0.029597 (0.00304)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.168974 (0.11159)	0.030322 (0.00310)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	-0.868900 (0.29795)	-0.061922 (0.00828)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	-0.005623 (0.14210)	0.036721 (0.00395)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	0.023177 (0.04944)	0.002419 (0.04616)	0.020479 (0.23075)	0.485440 (0.17819)	-0.011590 (0.02188)	-0.415073 (0.21412)
D(LRHPI)	-0.120831 (0.02976)	0.015411 (0.02778)	0.546304 (0.13889)	-0.053780 (0.10725)	-0.005188 (0.01317)	-0.364891 (0.12888)
D(LCPI)	0.026648 (0.01527)	-0.036926 (0.01425)	-0.382368 (0.07126)	0.154816 (0.05503)	0.010088 (0.00676)	0.223455 (0.06613)
D(LRIN)	-0.061245 (0.03680)	0.077666 (0.03436)	0.435017 (0.17177)	-0.624190 (0.13265)	-0.007402 (0.01629)	0.044197 (0.15939)
D(LRPR)	0.153891 (0.08574)	-0.229806 (0.08005)	-0.382236 (0.40019)	0.403493 (0.30904)	-0.117417 (0.03795)	0.004092 (0.37134)
D(LRGDP)	-0.071972 (0.02722)	0.040239 (0.02541)	0.497815 (0.12703)	-0.010006 (0.09809)	-0.030639 (0.01205)	-0.480060 (0.11787)
D(LRCON)	-0.000680 (0.02093)	0.026215 (0.01954)	0.270176 (0.09770)	-0.199498 (0.07545)	-0.028250 (0.00926)	-0.115690 (0.09066)
D(LRSVA)	-8.628788 (5.26833)	-4.076100 (4.91842)	7.214589 (24.5890)	-25.24146 (18.9884)	2.312040 (2.33162)	15.37806 (22.8167)

7 Cointegrating Equation(s): Log likelihood 2078.259

Normalized cointegrating coefficients (standard error in parentheses)

LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSVA
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.012989 (0.00193)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.057030 (0.00469)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.032582 (0.00692)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.030864 (0.00312)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	-0.064705 (0.00911)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.036703 (0.00348)
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	-0.003203 (0.00607)

Adjustment coefficients (standard error in parentheses)

D(LRHD)	-0.014863	0.022140	-0.140075	0.511446	-0.003637	-0.341392	-0.086266
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	(0.05353)	(0.04687)	(0.24584)	(0.17599)	(0.02203)	(0.21507)	(0.23853)
D(LRHPI)	-0.128810	0.019547	0.512627	-0.048325	-0.003520	-0.349435	0.486130
	(0.03268)	(0.02861)	(0.15009)	(0.10745)	(0.01345)	(0.13131)	(0.14563)
D(LCPI)	0.031851	-0.039623	-0.360408	0.151259	0.009000	0.213377	-0.316129
	(0.01675)	(0.01466)	(0.07692)	(0.05507)	(0.00689)	(0.06730)	(0.07464)
D(LRIN)	-0.044034	0.068744	0.507660	-0.635957	-0.011000	0.010860	0.401107
	(0.04026)	(0.03525)	(0.18490)	(0.13236)	(0.01657)	(0.16176)	(0.17940)
D(LRPR)	0.175852	-0.241191	-0.289543	0.388480	-0.122008	-0.038447	-0.087521
	(0.09418)	(0.08246)	(0.43256)	(0.30966)	(0.03876)	(0.37842)	(0.41970)
D(LRGDP)	-0.070934	0.039701	0.502195	-0.010715	-0.030856	-0.482070	0.507411
	(0.02995)	(0.02622)	(0.13754)	(0.09846)	(0.01232)	(0.12033)	(0.13345)
D(LRCON)	-0.007423	0.029711	0.241713	-0.194887	-0.026841	-0.102627	0.207276
	(0.02297)	(0.02011)	(0.10549)	(0.07552)	(0.00945)	(0.09229)	(0.10236)
D(LRSAV)	-10.19788	-3.262652	0.592008	-24.16878	2.640076	18.41730	-5.947019
	(5.78341)	(5.06368)	(26.5612)	(19.0147)	(2.38014)	(23.2372)	(25.7718)

APPENDIX B: VECM Estimates with one equation

Vector Error Correction Estimates

Date: 12/18/12 Time: 15:33

Sample (adjusted): 1985Q4 2012Q1

Included observations: 106 after adjustments

Standard errors in () & t-statistics in []

CointegratingEq:	CointEq1
LRHD(-1)	1.000000
LRHPI(-1)	-0.538606 (0.78786) [-0.68363]
LCPI(-1)	-20.13977 (4.07705) [-4.93979]
LRIN(-1)	7.245861 (3.08554) [2.34833]
LRPR(-1)	0.720166 (0.36405) [1.97822]
LRGDP(-1)	11.29535 (3.60659) [3.13187]
LRCON(-1)	-18.38194 (4.12142) [-4.46010]
LRSAP(-1)	-0.023441 (0.01804) [-1.29937]
C	80.37683
Error Correction:	D(LRHD) D(LRHPI) D(LCPI) D(LRIN) D(LRPR) D(LRGDP) D(LRCON) D(LRSAV)

CointEq1	0.006288 (0.00685) [0.91794]	-0.016642 (0.00428) [-3.88780]	0.013878 (0.00206) [6.72719]	-0.012948 (0.00534) [-2.42515]	-0.022169 (0.01235) [-1.79486]	-0.009141 (0.00391) [-2.33781]	-0.013031 (0.00289) [-4.50473]	-0.161461 (0.77169) [-0.20923]
D(LRHD(-1))	0.123429 (0.17717) [0.69666]	0.133578 (0.11071) [1.20653]	-0.086789 (0.05336) [-1.62660]	0.026500 (0.13809) [0.19191]	0.165406 (0.31944) [0.51779]	0.164501 (0.10113) [1.62665]	0.169844 (0.07482) [2.27017]	-6.188804 (19.9584) [-0.31009]
D(LRHD(-2))	0.074312 (0.16320) [0.45534]	0.094007 (0.10198) [0.92180]	-0.024116 (0.04915) [-0.49067]	0.308873 (0.12720) [2.42826]	0.371285 (0.29425) [1.26179]	0.095970 (0.09315) [1.03023]	-0.006123 (0.06892) [-0.08885]	-15.67299 (18.3845) [-0.85251]
D(LRHPI(-1))	0.247621 (0.19474) [1.27157]	0.998311 (0.12169) [8.20384]	-0.003486 (0.05865) [-0.05944]	0.047410 (0.15178) [0.31236]	0.269591 (0.35111) [0.76782]	0.091646 (0.11115) [0.82449]	0.023830 (0.08223) [0.28979]	12.84737 (21.9369) [0.58565]
D(LRHPI(-2))	-0.045545 (0.20975) [-0.21713]	-0.262639 (0.13107) [-2.00377]	-0.003499 (0.06317) [-0.05540]	0.009799 (0.16348) [0.05994]	-0.044540 (0.37819) [-0.11777]	-0.058644 (0.11973) [-0.48982]	0.014272 (0.08857) [0.16113]	-14.00775 (23.6286) [-0.59283]
D(LCPI(-1))	-0.022836 (0.63273) [-0.03609]	1.223895 (0.39539) [3.09544]	0.026468 (0.19055) [0.13891]	0.956522 (0.49315) [1.93960]	3.049495 (1.14082) [2.67308]	0.771491 (0.36116) [2.13616]	0.241496 (0.26719) [0.90385]	-2.729964 (71.2766) [-0.03830]
D(LCPI(-2))	-0.534180 (0.66799) [-0.79968]	0.052256 (0.41742) [0.12519]	-0.303630 (0.20117) [-1.50934]	1.044089 (0.52064) [2.00541]	1.313879 (1.20440) [1.09090]	0.484196 (0.38128) [1.26991]	0.373108 (0.28208) [1.32272]	21.68844 (75.2488) [0.28822]
D(LRIN(-1))	0.701568 (0.24254) [2.89256]	0.196097 (0.15156) [1.29385]	-0.159573 (0.07304) [-2.18468]	-0.284089 (0.18904) [-1.50281]	0.472759 (0.43730) [1.08107]	0.022806 (0.13844) [0.16473]	0.240946 (0.10242) [2.35254]	-11.16468 (27.3222) [-0.40863]
D(LRIN(-2))	0.433146 (0.23575) [1.83729]	0.214036 (0.14732) [1.45288]	-0.035120 (0.07100) [-0.49467]	0.102536 (0.18375) [0.55803]	0.604373 (0.42506) [1.42184]	0.072553 (0.13457) [0.53916]	-0.000298 (0.09955) [-0.00300]	-23.67790 (26.5573) [-0.89158]
D(LRPR(-1))	0.091091 (0.06034) [1.50970]	-0.115782 (0.03770) [-3.07082]	0.038064 (0.01817) [2.09479]	-0.147930 (0.04703) [-3.14564]	0.345799 (0.10879) [3.17865]	-0.048480 (0.03444) [-1.40767]	-0.031663 (0.02548) [-1.24272]	-5.045659 (6.79692) [-0.74234]
D(LRPR(-2))	0.050198 (0.05718) [0.87787]	-0.003693 (0.03573) [-0.10334]	0.017783 (0.01722) [1.03266]	-0.025243 (0.04457) [-0.56640]	-0.059565 (0.10310) [-0.57775]	-0.047358 (0.03264) [-1.45097]	-0.038132 (0.02415) [-1.57923]	4.138263 (6.44143) [0.64244]
D(LRGDP(-1))	-0.515608 (0.24658) [-2.09106]	0.073560 (0.15408) [0.47741]	0.030596 (0.07426) [0.41203]	0.332346 (0.19218) [1.72932]	0.858484 (0.44458) [1.93100]	-0.171994 (0.14074) [-1.22203]	-0.023883 (0.10412) [-0.22937]	4.374706 (27.7767) [0.15750]
D(LRGDP(-2))	-0.362790 (0.23785) [-1.52528]	0.101753 (0.14863) [0.68460]	-0.054360 (0.07163) [-0.75890]	0.257953 (0.18538) [1.39146]	-0.200690 (0.42885) [-0.46797]	-0.011988 (0.13576) [-0.08830]	0.013252 (0.10044) [0.13194]	6.824343 (26.7938) [0.25470]
D(LRCON(-1))	0.072184 (0.45298) [0.15935]	0.323611 (0.28306) [1.14326]	-0.186500 (0.13641) [-1.36715]	0.629612 (0.35305) [1.78334]	0.395960 (0.81672) [0.48482]	0.836015 (0.25856) [3.23340]	0.520911 (0.19128) [2.72327]	-15.98418 (51.0275) [-0.31325]
D(LRCON(-2))	-0.293754 (0.44249) [-0.66386]	-0.145347 (0.27651) [-0.52565]	0.027116 (0.13326) [0.20348]	0.283802 (0.34488) [0.82290]	1.388448 (0.79782) [1.74030]	0.075934 (0.25257) [0.30064]	0.092287 (0.18685) [0.49390]	28.83107 (49.8466) [0.57840]
D(LRSAV(-1))	-0.000564 (0.00100)	-0.000959 (0.00063)	0.000601 (0.00030)	-0.000330 (0.00078)	0.001202 (0.00181)	0.000800 (0.00057)	-0.000768 (0.00042)	-0.387130 (0.11296)

		[-0.56250]	[-1.52991]	[1.99022]	[-0.42223]	[0.66464]	[1.39818]	[-1.81275]	[-3.42727]
D(LRSAV(-2))	-0.001369 (0.00103) [-1.32446]	-0.000978 (0.00065) [-1.51527]	0.000677 (0.00031) [2.17392]	-0.000410 (0.00081) [-0.50898]	0.001359 (0.00186) [0.72935]	0.000290 (0.00059) [0.49130]	-0.000659 (0.00044) [-1.50975]	-0.100227 (0.11640) [-0.86102]	
C	0.011959 (0.01700) [0.70357]	-0.033389 (0.01062) [-3.14365]	0.028978 (0.00512) [5.66126]	-0.031349 (0.01325) [-2.36641]	-0.105887 (0.03065) [-3.45522]	-0.008389 (0.00970) [-0.86474]	-0.022877 (0.00718) [-3.18741]	-0.206702 (1.91469) [-0.10796]	
R-squared	0.387470	0.736127	0.711511	0.341098	0.527196	0.313485	0.674722	0.176062	
Adj. R-squared	0.269140	0.685152	0.655780	0.213810	0.435859	0.180862	0.611884	0.016892	
Sum sq. resids	0.053423	0.020861	0.004845	0.032453	0.173670	0.017405	0.009526	677.9324	
S.E. equation	0.024639	0.015397	0.007420	0.019204	0.044424	0.014064	0.010404	2.775568	
F-statistic	3.274490	14.44082	12.76691	2.679736	5.771984	2.363741	10.73752	1.106126	
Log likelihood	252.0188	301.8582	379.2338	278.4366	189.5365	311.4562	343.4011	-248.7547	
Akaike AIC	-4.415449	-5.355815	-6.815733	-4.913899	-3.236537	-5.536910	-6.139644	5.033108	
Schwarz SC	-3.963167	-4.903533	-6.363451	-4.461617	-2.784255	-5.084628	-5.687362	5.485390	
Mean dependent	0.002502	0.004094	0.020917	0.009328	-0.028683	0.009141	-0.012788	-0.145310	
S.D. dependent	0.028821	0.027439	0.012647	0.021658	0.059146	0.015539	0.016701	2.799312	
Determinant resid covariance (dof adj.)		2.54E-26							
Determinant resid covariance		5.73E-27							
Log likelihood		1999.201							
Akaike information criterion		-34.85285							
Schwarz criterion		-31.03358							

APPENDIX C: Vector Error Correction Model Estimates with two equations

Vector Error Correction Estimates

Date: 12/19/12 Time: 11:17

Sample (adjusted): 1985Q4 2012Q1

Included observations: 106 after adjustments

Standard errors in () & t-statistics in []

Cointegration Restrictions:

B(1,1)=1, B(2,1)=1

Convergence achieved after 38 iterations.

Not all cointegrating vectors are identified

Restrictions are not binding (LR test not available)

CointegratingEq:	CointEq1	CointEq2
LRHD(-1)	1.000000	1.000000
LRHPI(-1)	-0.515140	-0.191923
LCPI(-1)	-16.95094	26.96861
LRIN(-1)	5.625555	-16.69044
LRPR(-1)	0.546350	-1.847587
LRGDP(-1)	9.850050	-10.05616
LRCON(-1)	-15.52590	23.81018
LRSV(-1)	-0.019160	0.039805

Error Correction:	D(LRHD)	D(LRHPI)	D(LCPI)	D(LRIN)	D(LRPR)	D(LRGDP)	D(LRCON)	D(LRSAV)
CointEq1	-0.036499 (0.02998) [-1.21756]	-0.073274 (0.01795) [-4.08153]	0.024901 (0.00907) [2.74408]	0.003401 (0.02358) [0.14424]	0.093409 (0.05318) [1.75656]	-0.046951 (0.01683) [-2.78911]	-0.002139 (0.01275) [-0.16773]	1.455278 (3.41485) [0.42616]
CointEq2	-0.019152 (0.01258) [-1.52244]	-0.022752 (0.00753) [-3.02011]	0.003322 (0.00381) [0.87243]	0.008415 (0.00990) [0.85033]	0.052272 (0.02232) [2.34244]	-0.015395 (0.00706) [-2.17938]	0.006064 (0.00535) [1.13323]	0.715736 (1.43300) [0.49947]
D(LRHD(-1))	0.115770 (0.17604) [0.65764]	0.123762 (0.10543) [1.17393]	-0.085015 (0.05329) [-1.59534]	0.029562 (0.13849) [0.21347]	0.186160 (0.31228) [0.59613]	0.157922 (0.09885) [1.59753]	0.171940 (0.07488) [2.29611]	-5.900413 (20.0535) [-0.29423]
D(LRHD(-2))	0.030388 (0.16476) [0.18444]	0.037712 (0.09867) [0.38221]	-0.013943 (0.04987) [-0.27956]	0.326435 (0.12961) [2.51860]	0.490315 (0.29226) [1.67764]	0.058240 (0.09252) [0.62950]	0.005901 (0.07008) [0.08421]	-14.01894 (18.7682) [-0.74695]
D(LRHPI(-1))	0.147407 (0.20481) [0.71973]	0.869871 (0.12265) [7.09202]	0.019724 (0.06200) [0.31814]	0.087478 (0.16112) [0.54294]	0.541163 (0.36331) [1.48952]	0.005564 (0.11501) [0.04838]	0.051264 (0.08712) [0.58842]	16.62118 (23.3307) [0.71242]
D(LRHPI(-2))	-0.100637 (0.21159) [-0.47562]	-0.333247 (0.12672) [-2.62987]	0.009260 (0.06405) [0.14457]	0.031826 (0.16645) [0.19120]	0.104755 (0.37535) [0.27909]	-0.105967 (0.11882) [-0.89185]	0.029354 (0.09001) [0.32613]	-11.93312 (24.1033) [-0.49508]
D(LCPI(-1))	-0.123364 (0.63204) [-0.19518]	1.095053 (0.37851) [2.89304]	0.049751 (0.19133) [0.26003]	0.996715 (0.49721) [2.00462]	3.321919 (1.12119) [2.96285]	0.685139 (0.35492) [1.93042]	0.269016 (0.26886) [1.00059]	1.055617 (71.9986) [0.01466]
D(LCPI(-2))	-0.535907 (0.66344) [-0.80777]	0.050042 (0.39732) [0.12595]	-0.303230 (0.20083) [-1.50987]	1.044779 (0.52191) [2.00184]	1.318560 (1.17689) [1.12038]	0.482712 (0.37255) [1.29570]	0.373580 (0.28221) [1.32376]	21.75345 (75.5753) [0.28784]
D(LRIN(-1))	0.579422 (0.25450) [2.27667]	0.039549 (0.15242) [0.25948]	-0.131284 (0.07704) [-1.70407]	-0.235253 (0.20021) [-1.17502]	0.803765 (0.45147) [1.78034]	-0.082115 (0.14291) [-0.57458]	0.274383 (0.10826) [2.53449]	-6.564991 (28.9916) [-0.22644]
D(LRIN(-2))	0.301030 (0.25043) [1.20206]	0.044709 (0.14998) [0.29811]	-0.004522 (0.07581) [-0.05965]	0.155359 (0.19701) [0.78860]	0.962398 (0.44424) [2.16639]	-0.040933 (0.14063) [-0.29107]	0.035869 (0.10653) [0.33671]	-18.70274 (28.5275) [-0.65560]
D(LRPR(-1))	0.098036 (0.06011) [1.63102]	-0.106881 (0.03600) [-2.96917]	0.036455 (0.01820) [2.00355]	-0.150707 (0.04728) [-3.18722]	0.326978 (0.10663) [3.06660]	-0.042514 (0.03375) [-1.25958]	-0.033564 (0.02557) [-1.31274]	-5.307200 (6.84709) [-0.77510]
D(LRPR(-2))	0.030563 (0.05831) [0.52419]	-0.028857 (0.03492) [-0.82643]	0.022330 (0.01765) [1.26517]	-0.017393 (0.04587) [-0.37920]	-0.006357 (0.10343) [-0.06146]	-0.064223 (0.03274) [-1.96155]	-0.032757 (0.02480) [-1.32076]	4.877645 (6.64185) [0.73438]
D(LRGDP(-1))	-0.383873 (0.26042) [-1.47404]	0.242398 (0.15596) [1.55424]	8.54E-05 (0.07883) [0.00108]	0.279675 (0.20487) [1.36516]	0.501493 (0.46197) [1.08556]	-0.058836 (0.14624) [-0.40233]	-0.059946 (0.11078) [-0.54114]	-0.586128 (29.6657) [-0.01976]
D(LRGDP(-2))	-0.254501 (0.24720) [-1.02955]	0.240541 (0.14804) [1.62485]	-0.079440 (0.07483) [-1.06161]	0.214657 (0.19446) [1.10385]	-0.494144 (0.43851) [-1.12688]	0.081030 (0.13881) [0.58375]	-0.016393 (0.10515) [-0.15590]	2.746440 (28.1592) [0.09753]
D(LRCON(-1))	0.134692	0.403725	-0.200977	0.604620	0.226567	0.889709	0.503799	-18.33808

	(0.45185)	(0.27060)	(0.13678)	(0.35546)	(0.80154)	(0.25373)	(0.19221)	(51.4720)
	[0.29809]	[1.49196]	[-1.46935]	[1.70097]	[0.28266]	[3.50650]	[2.62115]	[-0.35627]
D(LRCON(-2))	-0.171535	0.011294	-0.001191	0.234936	1.057245	0.180918	0.058830	24.22865
	(0.44709)	(0.26775)	(0.13534)	(0.35172)	(0.79311)	(0.25106)	(0.19018)	(50.9304)
	[-0.38367]	[0.04218]	[-0.00880]	[0.66797]	[1.33304]	[0.72061]	[0.30933]	[0.47572]
D(LRSAV(-1))	-0.000483	-0.000855	0.000582	-0.000362	0.000983	0.000869	-0.000790	-0.390166
	(0.00100)	(0.00060)	(0.00030)	(0.00078)	(0.00177)	(0.00056)	(0.00042)	(0.11361)
	[-0.48470]	[-1.43197]	[1.92877]	[-0.46166]	[0.55570]	[1.55249]	[-1.86122]	[-3.43414]
D(LRSAV(-2))	-0.001175	-0.000731	0.000632	-0.000487	0.000835	0.000456	-0.000712	-0.107505
	(0.00103)	(0.00062)	(0.00031)	(0.00081)	(0.00184)	(0.00058)	(0.00044)	(0.11784)
	[-1.13616]	[-1.17951]	[2.01737]	[-0.59867]	[0.45508]	[0.78462]	[-1.61731]	[-0.91228]
C	0.017036	-0.026882	0.027802	-0.033379	-0.119646	-0.004028	-0.024267	-0.397902
	(0.01722)	(0.01031)	(0.00521)	(0.01355)	(0.03055)	(0.00967)	(0.00733)	(1.96192)
	[0.98915]	[-2.60627]	[5.33266]	[-2.46363]	[-3.91619]	[-0.41649]	[-3.31241]	[-0.20281]
R-squared	0.402657	0.763650	0.715742	0.345397	0.553679	0.352035	0.678112	0.178345
Adj. R-squared	0.279069	0.714750	0.656929	0.209962	0.461337	0.217974	0.611514	0.008347
Sum sq. resids	0.052099	0.018685	0.004774	0.032241	0.163942	0.016428	0.009427	676.0539
S.E. equation	0.024471	0.014655	0.007408	0.019251	0.043410	0.013741	0.010409	2.787604
F-statistic	3.258060	15.61659	12.16997	2.550278	5.995951	2.625920	10.18223	1.049102
Log likelihood	253.3495	307.6964	380.0169	278.7836	192.5915	314.5192	343.9563	-248.6077
Akaike AIC	-4.421689	-5.447102	-6.811639	-4.901577	-3.275312	-5.575834	-6.131251	5.049201
Schwarz SC	-3.944280	-4.969693	-6.334230	-4.424168	-2.797903	-5.098425	-5.653843	5.526610
Mean dependent	0.002502	0.004094	0.020917	0.009328	-0.028683	0.009141	-0.012788	-0.145310
S.D. dependent	0.028821	0.027439	0.012647	0.021658	0.059146	0.015539	0.016701	2.799312
Determinant resid covariance (dof adj.)		1.71E-26						
Determinant resid covariance		3.52E-27						
Log likelihood		2025.069						
Akaike information criterion		-35.03903						
Schwarz criterion		-30.81773						

APPENDIX D: Portmanteau autocorrelation LM test

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Date: 12/18/12 Time: 15:47

Sample: 1985Q1 2012Q1

Included observations: 106

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	8.840765	NA*	8.924962	NA*	NA*
2	35.27100	NA*	35.86347	NA*	NA*
3	87.68878	0.9567	89.80798	0.9393	112
4	143.7926	0.9639	148.1119	0.9379	176
5	200.2326	0.9710	207.3460	0.9374	240
6	265.5903	0.9453	276.6251	0.8682	304
7	311.4975	0.9852	325.7784	0.9447	368
8	363.4461	0.9928	381.9677	0.9599	432
9	433.7520	0.9795	458.7968	0.8831	496
10	501.4741	0.9636	533.5732	0.7830	560
11	580.5515	0.8926	621.8070	0.5173	624
12	638.0689	0.9134	686.6671	0.5072	688

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

APPENDIX E: VEC Residual Heteroskedasticity Tests (No Cross Terms)

VEC Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)

Date: 12/18/12 Time: 15:48

Sample: 1985Q1 2012Q1

Included observations: 106

Joint test:

Chi-sq	df	Prob
1375.000	1296	0.0625

APPENDIX F: VEC Residual Normality Test

VEC Residual Normality Tests

Orthogonalization: Residual Correlation (Doornik-Hansen)

Null Hypothesis: residuals are multivariate normal

Date: 12/18/12 Time: 15:48

Sample: 1985Q1 2012Q1

Included observations: 106

Component	Skewness	Chi-sq	df	Prob.
1	-0.605592	6.405134	1	0.0114
2	0.121047	0.289776	1	0.5904
3	0.197496	0.763906	1	0.3821
4	1.259715	20.88512	1	0.0000
5	1.314054	22.17580	1	0.0000
6	-0.055923	0.062141	1	0.8031
7	0.075886	0.114302	1	0.7353
8	-3.614337	71.11705	1	0.0000
Joint		121.8132	8	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	8.020464	44.51898	1	0.0000
2	3.199278	0.825373	1	0.3636
3	3.381961	1.380450	1	0.2400
4	9.230059	14.28377	1	0.0002
5	11.68064	36.74994	1	0.0000
6	3.377172	1.865429	1	0.1720
7	3.963088	6.328359	1	0.0119
8	24.84363	77.12372	1	0.0000
Joint		183.0760	8	0.0000

Component	Jarque-Bera	df	Prob.
1	50.92411	2	0.0000
2	1.115149	2	0.5726
3	2.144356	2	0.3423
4	35.16890	2	0.0000
5	58.92574	2	0.0000
6	1.927570	2	0.3814
7	6.442661	2	0.0399
8	148.2408	2	0.0000
Joint	304.8892	16	0.0000

APPENDIX G: Variance Decomposition

Variance Decomposition of LRHD, LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON and LRSV respectively

Period	Variance Decomposition of LRHD								
	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSV
1	0.024471	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.031223	88.92318	1.473409	0.163535	4.212064	1.302499	3.457596	0.272228	0.195489
3	0.036837	75.89899	4.265556	0.234598	8.655022	1.195579	5.795850	1.213579	2.740829
4	0.043653	66.90407	7.008784	0.217436	12.39123	0.856840	5.411779	3.148408	4.061450
5	0.051134	58.54008	10.75986	0.300875	15.43886	0.625463	4.933418	4.945819	4.455619
6	0.058977	49.98270	15.20424	0.327485	17.61190	0.502627	4.805389	6.664717	4.900948
7	0.067158	42.60018	19.15326	0.345067	18.94589	0.518190	4.623981	8.387747	5.425684
8	0.075501	36.60348	22.35751	0.382959	19.71860	0.629116	4.478276	10.00328	5.826778
9	0.083835	31.65469	25.02347	0.433079	20.15683	0.779948	4.455205	11.37408	6.122706
10	0.092099	27.53325	27.27240	0.494476	20.35061	0.944948	4.517012	12.51055	6.376762
11	0.100252	24.12129	29.15853	0.573012	20.38633	1.108063	4.607663	13.46029	6.584822
12	0.108269	21.28095	30.75203	0.667771	20.33244	1.258196	4.713016	14.25759	6.738017
13	0.116146	18.89054	32.11364	0.772884	20.22554	1.392162	4.828991	14.92840	6.847845
14	0.123888	16.86438	33.28372	0.883854	20.08608	1.510730	4.946917	15.49700	6.927315
15	0.131495	16.13842	34.29355	0.997852	19.92930	1.615165	5.060146	15.98254	6.983032

Period	Variance Decomposition of LRHPI								
	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSV
1	0.014655	0.007901	99.99210	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.031038	0.011742	93.58738	1.420419	0.007010	1.969071	0.064580	2.855338	0.084456
3	0.048215	0.290855	86.06063	2.225576	0.002944	4.264899	0.183881	6.462898	0.508319
4	0.065089	1.186039	80.12877	2.497972	0.006102	5.681325	0.792826	9.004921	0.702041
5	0.081425	2.318359	75.18104	2.742732	0.022386	6.610081	1.735423	10.49176	0.898220
6	0.097284	3.485930	70.95629	3.208398	0.068540	7.116169	2.747649	11.35593	1.061092
7	0.112571	4.544475	67.56927	3.862741	0.134726	7.298473	3.674223	11.77152	1.144573
8	0.127398	5.526593	64.82163	4.598133	0.213306	7.278120	4.485886	11.91969	1.156634
9	0.141790	6.408884	62.54568	5.332428	0.296057	7.162768	5.173567	11.94490	1.135723
10	0.155737	7.188892	60.61959	6.027732	0.379721	7.010685	5.751644	11.92301	1.098728
11	0.169224	7.867560	58.97379	6.666060	0.461822	6.850247	6.245170	11.87942	1.055931
12	0.182248	8.454709	57.55760	7.243207	0.542296	6.694379	6.672199	11.82327	1.012343
13	0.194808	8.956640	56.33543	7.762464	0.621084	6.549162	7.044109	11.76039	0.970731
14	0.206907	9.383180	55.27576	8.229614	0.698309	6.416541	7.370028	11.69488	0.931692
15	0.218556	9.744485	54.35175	8.650119	0.773946	6.296701	7.658296	11.62923	0.895480

Variance
Decomposition of

LCPI:

Period

d	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAB
1	0.007408	1.404928	26.24528	72.34979	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.012455	2.111797	24.44733	64.68849	0.007421	2.577588	1.203122	4.732259	0.231993
3	0.016688	2.918602	21.19876	53.27398	0.081067	7.115043	2.593309	10.59207	2.227174
4	0.020212	3.327746	19.85776	45.35204	0.489176	9.376631	5.432348	13.11753	3.046775
5	0.023306	3.702456	19.63719	39.71883	1.255432	10.50244	8.411817	13.45240	3.319440
6	0.026152	4.166667	19.46346	34.92057	2.441139	11.15935	10.96616	13.47649	3.406158
7	0.028767	4.786172	18.93059	30.92712	3.915900	11.51847	13.17222	13.43428	3.315262
8	0.031234	5.403835	18.07820	27.59253	5.649986	11.61047	15.33291	13.22384	3.108224
9	0.033615	6.071935	16.99297	24.75319	7.625913	11.50270	17.37185	12.81495	2.866487
10	0.035948	6.873445	15.76336	22.28900	9.815472	11.24053	19.15696	12.24935	2.611880
11	0.038265	7.840431	14.46355	20.12765	12.14864	10.85520	20.64506	11.56422	2.355263
12	0.040600	8.954340	13.15099	18.21729	14.55799	10.37772	21.83374	10.79822	2.109723
13	0.042983	10.20346	11.87127	16.51702	16.97940	9.835829	22.72033	9.987399	1.885285
14	0.045439	11.57366	10.66457	14.99452	19.35508	9.251238	23.31198	9.161804	1.687145
15	0.047988	13.04335	9.564385	13.62551	21.63264	8.641868	23.62837	8.345947	1.517934

Variance

Decomposition

of

LRIN:

Period

d	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAB
1	0.019251	59.52095	2.962136	9.812744	27.70417	0.000000	0.000000	0.000000	0.000000
2	0.025020	49.92020	4.691417	10.75674	23.94922	5.596507	2.752249	2.324957	0.008711
3	0.029385	37.59634	6.327551	10.76815	26.12911	8.935123	4.212360	5.937884	0.093479
4	0.034060	32.37993	9.005213	11.31922	25.89894	10.15762	3.572509	7.540309	0.126252
5	0.038816	28.24694	11.14393	11.85986	25.23515	11.48050	2.923021	8.559167	0.551422
6	0.043123	25.23823	12.56771	11.75230	24.43392	12.88675	2.601127	9.725202	0.794767
7	0.047068	22.99787	13.71417	11.51224	23.95649	13.89369	2.295963	10.65692	0.972657
8	0.050824	21.65470	14.69607	11.21499	23.39008	14.60813	2.006770	11.34021	1.089030
9	0.054369	20.66171	15.50293	10.88754	22.86245	15.19123	1.771663	11.89968	1.222792
10	0.057683	19.94678	16.17893	10.52777	22.37636	15.67277	1.584622	12.39969	1.313076
11	0.060808	19.41218	16.76756	10.17752	21.95311	16.05872	1.430090	12.82075	1.380087
12	0.063781	19.03389	17.28436	9.845004	21.55080	16.37468	1.300978	13.18101	1.429267
13	0.066610	18.73967	17.73524	9.537304	21.18127	16.64601	1.193042	13.49720	1.470261
14	0.069303	18.51170	18.12963	9.254164	20.83980	16.88312	1.102103	13.77911	1.500367
15	0.071874	18.32926	18.47624	8.997338	20.52656	17.09319	1.024843	14.02898	1.523584

Variance

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LRPR

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Period

d	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAB
1	0.043410	0.162948	0.973506	9.890773	3.373880	85.59889	0.000000	0.000000	0.000000
2	0.077832	0.050709	0.864980	17.14178	6.482041	73.49215	1.785520	0.011784	0.171043
3	0.108576	0.175068	0.459646	20.71065	10.09656	64.29723	3.332489	0.123383	0.804967
4	0.135584	0.772082	1.214082	20.46225	13.15369	57.72134	5.212986	0.397503	1.066072
5	0.159775	1.547540	3.022688	18.72679	15.86900	52.22846	6.600858	1.036103	0.968564
6	0.181812	2.309267	5.037636	16.79331	18.27258	47.14267	7.654213	1.994820	0.795506
7	0.202089	2.996157	6.914902	15.09261	20.28590	42.70641	8.250660	3.107186	0.646175
8	0.220871	3.547209	8.599740	13.70778	21.90039	39.02923	8.500614	4.170211	0.544824
9	0.238444	3.963700	10.10379	12.61881	23.16033	36.01483	8.540832	5.111368	0.486340

10	0.255041	4.266920	11.42980	11.78255	24.12953	33.52996	8.476177	5.929264	0.455796
11	0.270815	4.476067	12.59462	11.14619	24.88012	31.46871	8.353560	6.640219	0.440524
12	0.285854	4.605607	13.62256	10.66320	25.46653	29.74828	8.198112	7.262439	0.433264
13	0.300242	4.675891	14.53350	10.29670	25.92729	28.29799	8.027298	7.810661	0.430668
14	0.314053	4.704734	15.34411	10.01955	26.28967	27.06259	7.852678	8.296273	0.430399
15	0.327348	4.705509	16.06916	9.810531	26.57535	25.99990	7.680528	8.727888	0.431137

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	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAB
1	0.013741	0.010214	6.677943	19.63163	4.289393	1.803333	67.58749	0.000000	0.000000
2	0.019925	1.263109	8.628927	18.11756	4.317487	0.864946	57.38211	7.276642	2.149218
3	0.024973	1.269905	9.530885	17.19706	5.822224	1.330253	49.26734	13.91979	1.662544
4	0.029014	0.945160	12.10157	17.26901	5.894345	1.950056	41.90509	18.69742	1.237349
5	0.032687	0.779096	14.62762	16.96371	5.740911	2.597236	37.27131	21.00872	1.011385
6	0.036096	0.682957	16.98865	16.11855	5.425171	3.203596	33.85104	22.88055	0.849490
7	0.039231	0.599867	18.97453	15.26338	5.127892	3.735368	31.03904	24.52120	0.738727
8	0.042093	0.521919	20.60298	14.50663	4.826185	4.198369	28.67677	26.00741	0.659737
9	0.044703	0.462864	21.92056	13.81804	4.536937	4.598319	26.73302	27.32698	0.603287
10	0.047088	0.418378	23.03027	13.17403	4.261217	4.930193	25.13476	28.49497	0.556189
11	0.049283	0.383821	23.99741	12.58315	4.005360	5.200846	23.79942	29.51437	0.515630
12	0.051321	0.356098	24.84302	12.04596	3.767747	5.424563	22.66893	30.41400	0.479694
13	0.053225	0.332453	25.57282	11.56238	3.549362	5.613274	21.70329	31.21844	0.447985
14	0.055010	0.311782	26.19706	11.13021	3.349835	5.774812	20.87123	31.94506	0.420013
15	0.056687	0.293633	26.72806	10.74645	3.168852	5.914767	20.14955	32.60309	0.395600

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	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAB
1	0.010409	0.086505	23.71748	47.22178	1.857318	0.121604	4.102405	22.89290	0.000000
2	0.019122	1.443712	23.80587	40.76765	2.951177	0.700512	2.149085	27.73282	0.449166
3	0.027261	2.314771	24.03483	32.13762	2.606484	3.273206	1.179880	32.72377	1.729436
4	0.034747	3.382015	25.22631	26.83079	2.135819	5.174083	0.726540	33.90651	2.617939
5	0.041584	4.192225	26.81574	23.65679	1.675565	6.425750	0.564828	33.64230	3.026807
6	0.047897	4.879891	27.78278	21.35158	1.306505	7.402034	0.564033	33.39199	3.321190
7	0.053590	5.456617	28.13063	19.56704	1.044173	8.183289	0.677919	33.44546	3.494869
8	0.058670	5.985724	28.13624	18.16937	0.888495	8.770601	0.902068	33.56511	3.582398
9	0.063215	6.511196	27.97089	17.03000	0.839951	9.198077	1.202260	33.63852	3.609103
10	0.067324	7.104210	27.68108	16.06117	0.897421	9.497773	1.532445	33.63450	3.591403
11	0.071081	7.785002	27.28432	15.22279	1.057620	9.696702	1.868066	33.55363	3.531872
12	0.074563	8.559423	26.78364	14.49388	1.314385	9.816568	2.200369	33.38918	3.442551
13	0.077829	9.430326	26.18172	13.85616	1.663455	9.873722	2.522858	33.13810	3.333657
14	0.080932	10.40651	25.48510	13.29282	2.099482	9.878170	2.829627	32.79606	3.212235
15	0.083912	11.49102	24.70590	12.78985	2.616760	9.836344	3.116571	32.36115	3.082402

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V: Period	S.E.	LRHD	LRHPI	LCPI	LRIN	LRPR	LRGDP	LRCON	LRSAP
1	2.787604	5.046845	0.616584	0.375966	4.056466	0.192915	0.436795	7.139113	82.13532
2	3.270996	4.700719	0.448175	0.613287	3.236770	0.368059	0.490356	8.260704	81.88193
3	3.746709	4.664867	0.521733	1.095225	2.477859	0.313540	0.614414	7.862632	82.44973
4	4.245102	4.539192	0.878979	1.097813	1.988067	0.384601	0.774134	8.621811	81.71540
5	4.725591	4.655260	1.297511	1.091449	1.605892	0.414525	0.782477	9.040069	81.11282
6	5.159913	4.397147	1.838623	1.077381	1.346934	0.459759	0.880363	9.594813	80.40498
7	5.588836	4.145486	2.363094	1.047668	1.153158	0.546448	0.961510	10.11788	79.66475
8	6.000500	3.860443	2.878011	0.995067	1.006723	0.637519	1.047619	10.67471	78.89991
9	6.397871	3.587530	3.379760	0.938005	0.897149	0.721337	1.140973	11.15888	78.17636
10	6.780842	3.313636	3.874926	0.878180	0.811981	0.801555	1.238101	11.60603	77.47559
11	7.153084	3.060270	4.349440	0.818565	0.745591	0.877648	1.329931	12.01290	76.80565
12	7.513728	2.825614	4.803550	0.761291	0.693022	0.948245	1.418170	12.39189	76.15822
13	7.864709	2.611231	5.235571	0.707937	0.651550	1.013401	1.503689	12.73837	75.53825
14	8.206635	2.416355	5.645749	0.658740	0.618345	1.073779	1.585554	13.05783	74.94364
15	8.540389	2.240941	6.033879	0.613747	0.591936	1.129568	1.662895	13.35126	74.37578

Chol
esky
Orderi
ng:
LRHD
LRHP
LCPI
LRIN
LRPR
LRGD
P
LRCON
N
LRSAP
V

Cholesky ordering: LRHD, LRHPI, LCPI, LRIN, LRPR, LRGDP, LRCON, LRSAP

APPENDIX H: GIRF Results

