MACROECONOMIC CREDIT RISK MODEL FOR THE FINANCIAL SECTOR IN SRI LANKA

Dona Hansani Ireshika Wickramasinghe

(158386V)

Degree of Master of Science

Department of Mathematics

University of Moratuwa
Sri Lanka

December 2019

MACROECONOMIC CREDIT RISK MODEL FOR THE FINANCIAL SECTOR IN SRI LANKA

Dona Hansani Ireshika Wickramasinghe

(158386V)

Dissertation submitted in partial fulfillment of the requirements for the degree
Master of Science in Operational Research

Department of Mathematics

University of Moratuwa
Sri Lanka

December 2019

Declaration of the candidate

“I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Also, I hereby grant to University of Moratuwa the non-exclusive right to reproduce and distribute my thesis/dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature: Date:

The above candidate has carried out this research for the Master of Science in Operational Research under my supervision.

Signature of the Supervisor: Date:

Abstract

Economic development has a direct bearing on the credit quality of financial institutions. This study attempts to recognize this association of macroeconomic determinants and credit risk in the Sri Lankan banking sector by way of a macroeconomic credit risk model. The study employs a Vector Error Correction Model (VECM) to capture the relationship between macroeconomic variables namely the Real Gross Domestic Product (GDP), Unemployment Rate and Real Effective Exchange Rate (REER) with Non-Performing Loans (NPL), the proxy for default rates. The study uses data on Sri Lankan banking sector from 2009 to 2018 for the purpose. As of the findings Unemployment rate and Exchange Rate are found to be significant determinants of NPL. Unemployment Rate and Exchange rate is observed to have a significant positive association with Non-performing loans. Additionally, NPL itself is shown to have a significant feedback effect on credit default.

Key words: Non-performing loans, Macroeconomic determinants, Credit risk, Real GDP

Acknowledgement

At the completion of this dissertation it is with a great pleasure I convey my gratefulness for the dedication and admiration made by many individuals in making this a success.

It is my foremost duty to pay my gratitude to my supervisor Mr. Rohana Dissanayake, for his continuous support granted throughout. It was his gentle guidance with patience, motivation, enthusiasm, and immense knowledge encouraged me to accomplish the successful completion of this research.

Secondly, the support and guidance of Mr. T.M.J.A.Cooray, the course coordinator of the M.Sc in Operational Research is highly valued and appreciated. Moreover I am much grateful to the academic staff of the Department of Mathematics, University of Moratuwa and all the visiting staff members from other faculties and universities who provided guidance and encouragement by sharing their valuable knowledge throughout the course of the Masters degree program.

I would also wish to extend my gratitude to my superiors and work colleagues at my workplace, the Central Bank of Sri Lanka, for helping me out in different levels from the inception to the finalization of this research.

Finally, I owe my most sincere gratitude to my family members and all others those who supported me in various ways throughout this effort to make it a success.

Table of content

List of figures

List of tables

List of abbreviations

ADF - Augmented Dickey–Fuller

AIC - Akaike Information criteria

ARDL - Autoregressive Distributed-lagged

ARIMA – Auto Regressive Integrated Moving Average

ASPI – All Share Price Index

AWLR – Average Weighted Lending Rate

CPV - Credit Portfolio View

EDF – Expected Default Frequency

EXRT – Exchange Rate

FPE - Final Prediction Error

GDP – Gross Domestic Product

GNP – Gross National product

HQ - Hannan-Quinn information criterion

INF – Inflation

INT – Interest Rate

LLP – Loan Loss Provision

NPL – Non-Performing Loans

OLS – Ordinary Least Square

REER – Real Effective Exchange Rate

SD – Standard Deviation

SHRPRC – Share Price Index

SIC - Schwarz information criterion

UNEMP – Unemployment

VAR – Vector Autoregression

VECM - Vector Error Correction Model

List of Appendices

CHAPTER 1

INTRODUCTION

1.1 Background to the Study

A financial system refers to a set of financial institutions, financial markets, financial instruments and legal & regulatory framework that permits transactions to be made by extending credit (*World Bank*).The key role of a financial system is to facilitate the circulation of funds in an economy from surplus units to deficit units by way of financial assets. Financial institutions are generally the intermediaries in the system that facilitates this circulation of funds. Financial institutions include the banks, Non-Bank financial institutions, insurance companies, unit trusts, pension funds etc. They provide a platform to bring surplus and deficit units or the saving and borrowing units together and thereby to facilitate the flow of funds from savings to investments. A stable financial system is fundamental for an economy to grow as it has a direct bearing on the economic growth by way of facilitating this flow of funds. A stable financial system could mobilize savings for optimal productive investments which in return will create a favourable environment for the economic to grow.

However, this role of the financial system has been highly debated subsequent to the financial crises that have emerged in the recent past. Indeed, no country has avoided the experience of crisis or distress of the financial system at one time or another. Rather some have experienced multiple crises creating a huge negative impact on the financial system itself as well as on the economy. The recent well known example is the global financial crisis/ US subprime crisis which was a result of a asset price bubble driven by credit in the US housing market. Many economists identify this as the worst ever financial crisis after the Great Depression that occurred in 1930s. It headed financial institutions to incur severe losses leading to numerous bank failures. Further the implications were pretty worse that resulted the demise of the largest investment bank in the United States, Bear Stearns. These experiences have simulated economists to explore the factors that may give rise to crisis. Also, they have called attention to outrun a banking crises can have on the financial system and subsequently on the economy. As estimated by the International Monetary Fund (1999) the gross restructuring cost of a banking distress can be as significant as a half of a country's annual Gross Domestic Product. IMF identifies the resolution cost of banking crises in Chile and Argentina in early 1980s to be over 40% of GDP. Estimated recapitalization costs of banks in four affected countries in the Asian financial crisis have ranged from 10% (Malaysia) to 58% (Thailand) as a share of GDP (World Bank, 2000). These estimations give a clear picture on how severely a baking or a financial system crisis can affect the overall economy of a country. Additionally, credit tightening after crisis could further deteriorate the performance of an economy through misallocation and underutilization of funds. These serious economic consequences have aroused attention to look into proactive strategies to manage occurrence of crises. Accordingly, identifying the causes of distress or crisis through stress testing and early-warning systems is crucial in enabling institutions to be proactive.

Credit risk is the most relevant risk to a financial institution which could lead an institution into distress by affecting earnings and capital through nonpaid obligations. As defined by the Bank of International Settlements, credit risk is "the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms". Banks being financial institutions frequently dealing with lending will always have agreements going in default. Hence, credit risk is a central component of any financial institutions' risk management strategy accounting for up to 80% of a bank's total risk exposure (Assouan, 2012). Accordingly, identifying the factors that lead to increased credit risk is crucial for financial institutions to have a proper assessment on its vulnerabilities.

Literature identifies macroeconomic factors such as growth in gross domestic product, unemployment rate, inflation to have a direct impact on this credit risk component. As noticed by Llewellyn (2002), economic, financial and structural weaknesses have dealing in any banking crises. Most banking crises are preceded by changes in the economic environment. A banking crisis may occur as a result of volatility in the macroeconomic environment. Such developments could be a drop in economic growth or expansion, increases in interest rate and inflation, increase in levels of unemployment etc (Festic et al., 2011). Further hazardous banking practices, incentive structures, and moral hazard are few other issues that have the potential of leading to banking system problems (Llewellyn, 2002). Whatsoever, understanding the relationship between credit risk and these macroeconomic variables is crucial in developing appropriate strategies to achieve ultimate economic and financial stability objectives. An immense pressure is on the central banks as regulatory authorities of economic as well as financial systems, to provide timely assessment of the buildup of vulnerabilities from where most financial and economic crises originate.

Many countries including Sri Lanka has well established bank dominated financial systems where the whole system is dominated by the formal banking sector. In such a system, individuals predominately keep their savings in banks. Banks on the other hand are the main source of external financing to the corporate sector as well. Banks dominate the equity and corporate debt markets in terms of investments. Accordingly, performance of the banking sector directly affects the growth of such economies since majority of funds of flow through the banking sector. However, there are indirect flows of funds which cannot be taken into the formula as those flows out of the formal system.

In the Sri Lankan context, banking sector dominates the financial system with a market share of 60.3 per cent of total assets (excluding Central Bank Assets) amounting to more than Rs. 10 trillion by end 2017 (Central Bank of Sri Lanka Annual Report, 2017). With 26 Licensed Commercial Banks (LCBs) and 7 Licensed Specialized Banks (LSBs) the sector plays the key role in supporting economic growth by way of facilitating financial intermediation. It controls most of the financial flows and possesses most of the financial assets in the system (Table 1.1). Financial sector data since late 2017 show a clear vulnerability to credit risk with deterioration in asset quality (Financial System Stability review 2018, Central Bank of Sri Lanka).

Table 1.1: Total Assets of the Financial System (Provisional)

	Rs. Billion	Share (%)
Banking Sector	**11,897.4**	**69.8**
Central Bank	1,604.8	9.4
Licensed Commercial banks (LCBs)	8,926.4	52.3
Licensed Specialised Banks (LSBs)	1,366.2	8.0
Other Deposit Taking Institutions	**1,370.4**	**8.0**
Licensed Finance Companies (LFCs)	1227.5	7.2
Co-operative Rural Banks	132.7	0.8
Thrift and Credit Co-operative Societies	10.2	0.1
Specialised Financial Institutions	**388.9**	**2.3**
Specialised Leasing Companies (SLCs)	127.5	0.7
Primary Dealers	77.3	0.5
Stock Brokers	9.1	0.1
Unit Trusts / Unit Trust Management Companies	131.7	0.8
Market Intermediaries	28.7	0.2
Venture Capital Companies	14.6	0.1
Contractual Savings Institutions	**3395.8**	**19.9**
Insurance Companies	559.2	3.3
Employees' Provident Fund	2066.3	12.1
Employees' Trust Fund	279	1.6
Approved Pension and Provident Funds	437.3	2.6
Public Service Provident Fund	53.9	0.3
Total	**17,052.5**	**100**

Source: Annual Report 2017, Central Bank of Sri Lanka

Non-Performing Loans (NPL) of the banking sector are on a continuous growth while the growth in credit is declining over time (Figure1.1**)**. Delinquency of loans and advances has increased significantly with NPL volumes increasing to Rs.160 billion by December 2018.Year on year credit growth as at end August 2018 was 15.7 per cent in comparison to 16.1 per cent recorded by end 2017, displaying a clear deterioration in credit. Rescheduled loans are seen to show a 45% growth on year on year basis June 2018, which is yet another clear indication of asset quality deterioration. Rescheduling indicates the difficulty or inability of the borrower to repay the credit upon agreed terms which are prone to go NPLs requiring more write-offs and provisions later. Hence it is important to assess the relationship between factors that lead to deterioration of asset quality, increasing the vulnerability to credit risk which could provide an early warning on potential stress situations.

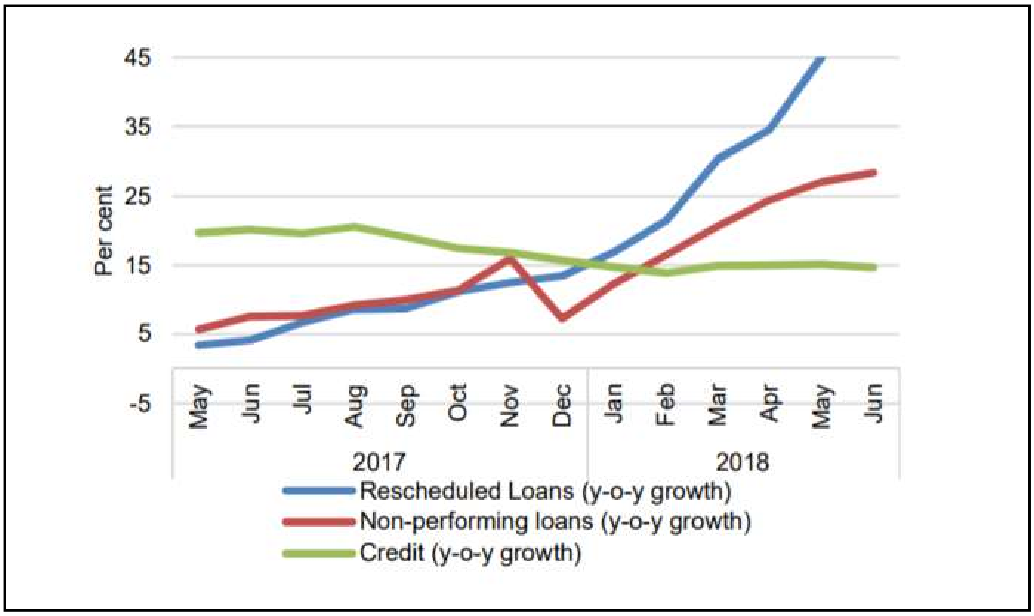


Figure 1.1: LCBs sector - Trend in Credit Growth, NPL Growth & Rescheduled loans

Source: Financial System Stability Review 2018, Central Bank of Sri Lanka

1.2 Research Problem

Today, in the Sri Lankan context the banking institutions are operating in an environment with a clear vulnerability to credit risk following incremental deterioration in asset quality. In such an environment managing the credit risk has become the hardest part for the institutions. Debt obligations defaulted by borrowers have made the role of financial intermediation challenging than ever before as the institutions will fail to recover what they have lent out. Adding to this, the experience after the global financial crisis has showed institutions, how poor credit risk management has led to deterioration in credit standing. Thus banks are faced with the challenge of understanding the causes of credit risk proactively to develop defensive strategies for risk management. It is through such a proactive understanding that banks can improve the resilience to plausible shocks and vulnerabilities.

In identifying the causes of credit risk to financial institutions, relationship between credit risk and macroeconomic variables is recognized as crucial as the behavior of borrowers' is identified to be sensitive to developments in the macro economy. The banking system plays a crucial role in a financial system of a country and so it is important to be able to predict the movement in the sector to changes in the economic environment to ensure its stability. Therefore identifying the macroeconomic indicators that can determine the changes in debtors' credit risk is important in overall credit risk management.

Accordingly, this study is focused on investigating the macroeconomic sources of credit risk in the Sri Lankan banking system. To be specific it aims at understanding the key macroeconomic variables that are linked to the banking sector loan quality as indicated by defaulted or non-performing loans.

In view of this, the specific the problem statement would be to understand;

"How macroeconomic variables affect banking sector credit risk in Sri Lanka".

1.3 Research Objectives

As clearly depicted by the problem statement above, this research is carried out focusing on identifying the relationship between macroeconomic variables and banking sector loan quality. Empirical research has clearly supported the strong relationship to exist between macroeconomic variables and systemic component of credit risk reflected by asset quality. There are well known credit portfolio models in literature that have tried to link this default quality migration to macroeconomic variables. Upon the guidance given by those literatures, the study was designed to identify macroeconomic determinants of banking sector loan quality in Sri Lanka byway of a best fitted model.

Accordingly, the specific objective of the study was;

- To develop a best fitted model to estimate the relationship between macroeconomic variables and banking sector credit risk in Sri Lanka

This model is expected to unveil the significant relationships between banking sector loan quality and macroeconomic variables by preserving the economic relationships with high explanatory power. It is expected to be useful to have a forward-looking assessment on how banks would react to adverse but predictable macroeconomic shocks in the economy.

1.4 Research Design

The research framework for the study was designed with careful review into literature. A quantitative approach was employed as statistical and computational tools were used to arrive at the specified objectives. Initially, the research interest and the focus were defined based on the working life experiences and exposures. Then a background study was conducted byway a reference to empirical research to understand the scope and the depth of the area of interest. Subsequently the focus was narrowed down to a specific objective and an extensive literature review was carried out to develop the study framework. The research was conducted upon this framework which is discussed in detail under Chapter 3.The research process is graphical illustrated in Figure 1.2 below.

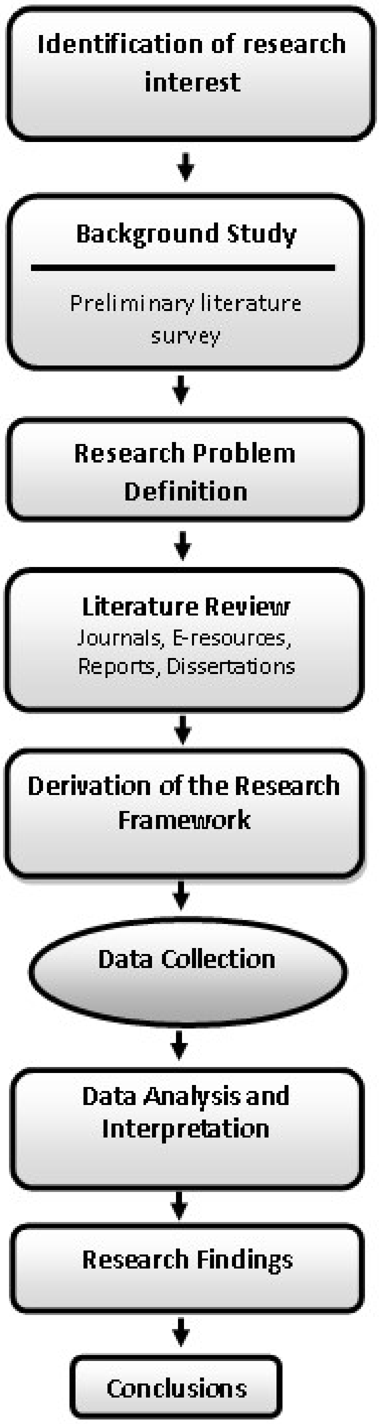


Figure 1.2: Research Process

1.5 Scope and Limitations

1.5.1 Scope of the study

As discussed, Sri Lankan financial system mainly comprises of Banks, Non-Bank Financial Institutions, Microfinance Institutions, Primary Dealers, Money Brokers and Money Changers. Banks in total hold 60.3% of total assets of the sector excluding the central bank assets. Based on the asset base and the functionality, Licensed Commercial Banks (LCBs), are the single most important category in the banking sector. Thus health of the system largely depends on the soundness of LCBs, and more specifically on the financial soundness of the six largest LCBs, identified as the Systemically Important Banks (SIBs). However, in an overall level the entire banking sector plays a critical role as it key responsibility is to provide liquidity to the economy. Given this dominant role of the banking sector and the significant representation of its asset base and accuracy and availability of data, the study is focused on assessing the relationship between banking sector loan quality and macroeconomic variables.

It is expected that this interpretation on the banking sector would provide a fair representation on the entire financial system.

1.5.2 Limitations

However, there were certain limitations and restrictions encountered when carrying out this study. The scope and the conduct were constrained to certain margins by these limitations.

i. Non availability of historical default rates

Similar to many other countries, the historical default rates are not readily available in the Sri Lankan context as well. Hence Non Performing Loans to Total Loans Ratio - NPL ratio had to be substituted as the dependent variable in model fitting, as commonly used in empirical research.

However, there was a limitation on availability of NPL data as well. Historical NPL data prior to 2009 was not available in public domains and hence the analysis had to be limited to 40 data points with quarterly data from 2009 -2018 period.

ii. Limitation on availability of individual bank level information

Yet another restriction was the limited availability of individual institutional level information. Literature identifies the factors affecting credit risk to be twofold as systemic factors and firm specific factors. A comprehensive detailing on this is given in Chapter 2. However, there were limitations in finding out firm specific data and thus the study was merely restricted to identifying the systemic determinants of credit risk.

iii. Limitation on availability of overall financial sector data

Though the Sri Lankan financial sector is predominantly dominated by the banks, there are other deposit taking and contractual savings institutions in the system. Licensed Finance Companies are a key segment in this. However, there is a serious concern on the accuracy and reliability of NPA data in this sector. Hence the study had to be restricted to the banking sector given the availability and quality of data.

iv. Restriction in data frequencies

This study employs data on quarterly frequency from 2009-2018. However, certain selected data were readily available on different frequencies and hence an additional effort had to be put to gather data in the preferred quarterly frequency.

v. Limited availability of empirical research in the local context

Though there are many empirical research conducted on this area in the international context, only few research studies are available with respect to the Sri Lankan market. Therefore, a comprehensive analysis on literature with an extra effort was required to be employed in defining the research framework and the outset.

Given these, the study is constrained to certain limitations and the research is designed within these boundaries.

1.6 Significance of the Study

The financial system in Sri Lanka has faced difficulties over the years. History has shown how lack of credit standards coupled with poor risk management strategies have lead institutions into trouble. As commonly understood, a major cause of many of these problems has been the credit risk arising by way of borrowers defaulting repayment of loans and advances.

Adding to this, recent financial sector statistics show a clear incremental growth in asset quality deterioration. NPLs are on a continuous growth followed by rescheduled loan volumes. With experience, it is known that most of the rescheduled loans are likely to fall into non performing category later. The increasing delinquency is further heightened with more and more new loans being added to the special mentioned category. Additionally, provision coverage ratios have eroded notably (Financial System Stability Report, 2018, Central Bank of Sri Lanka). All these signs alarm the adverse effects that could be on the bottom line of financial institutions hindering their earning capacities and profitability. Thus understanding the determinants of borrower default is paramount in improving the credit standing of institutions.

A proper and comprehensive understanding can help the institutions to develop suitable forward-looking risk mitigation strategies to manage the possible risk events at institutional level. Regulators would also need to assess the possible imbalances at the systemic level. Regulators need to be cautious of NPL patterns to put in place proper risk management mechanisms to mitigate risks emanating from increasing NPLs with a holistic view. Assessment of credit risk shall be crucially a major part of their mandate as maintenance of financial system stability is their key objective. Through proper assessment regulators could take prudential policy actions to curtail the buildup of systemic imbalances.

This study will provide a framework to comprehensively understand the macroeconomic causes of credit risk in the Sri Lankan banking sector. The findings will enable to understand the causal relationship between the selected macroeconomic variables and the borrower defaults. As discussed, this understanding is very much important for banking institutions as well as the regulators mainly the Central Bank. Hence it is believed that the outcome of this study will provide a guideline for banking institutions to assess the causes of default at the institutional level. It will enable the banks to have a methodical and a coherent understanding of how NPLs would vary with changes in the macro economy. Further, the model is expected to lay a foundation for stress testing for regulators at the systemic level. It is commonly understood that the banking institutions, the central bank and other regulatory institutions do credit risk stress testing to different extents to identify the buildup of vulnerabilities. However, the basis of these would be questionable as there may not be sound methodological and scientific foundation for these models given the limited availability of comprehensive research in this area. In such an environment this study is expected to provide a strong basis and a framework for credit risk stress testing in Sri Lanka.

Though this specific study is limited to the banking sector, the same research approach can be employed to assess the credit risk determinants in other subsectors such as non-bank financial institutions sector. Additionally, the outcome of this study can be used in future research in credit risk analysis. Research on credit risk analysis could be developed upon the framework laid down in this study. As discussed in detail under Chapter 3, the satellite credit risk model developed in this study can be used to develop macroeconomic model to link external shocks to macroeconomic variables as suggested by Cihak (2007).As the study findings identify the key determinants of defaults, the identified variables can be employed in stress testing to analyse the sensitivity to exceptional but plausible shocks. The study can be extended to be used for both micro and macro level stress testing purposes to assess the resilience at the individual institutional level as well as the systemic level. Accordingly, this would suitably be an initial approach to provide a direction for future studies in this arena.

In all these aspects this research has an academic value and its potential to furnish positive benefits as discussed, makes this a significant effort.

1.7 Organisation of the Dissertation

This dissertation consists of five individual chapters. This Introduction chapter is the first section where a preface to the study and the research background is provided. It provides an overview highlighting the research background, significance and the scope.

The second chapter is the Literature Review which gives an outline to previously published literature on the subject of interest. It basically highlights the research approaches and findings of previous literature upon which the framework for this specific study has been derived. Around 50 papers have been reviewed for the purpose and the second chapter provides a summary of this literature.

Chapter 3 is the Methodology where an overview to the research methodology is provided. It basically highlights the experimental framework adapted in this study. Study variables and relationships used in deriving conclusions are underlined in detail in this section. Further it presents the research approach with justifications. Data collection methods and data analysis &interpretation techniques used for the purpose are described in detail in the latter part of the chapter.

Chapters 4 exemplify the findings of this particular research. It presents an in-depth analysis in to the study variables with interpretations on how the research objectives are achieved.

The final chapter discusses conclusions and recommendations based on the analysis presented in chapter 4.

CHAPTER 2

LITERATUREREVIEW

2.1 An overview of Credit Risk Modeling

Risk taxonomy usually identifies many risk components among which market risk, credit risk and operational risk are categorized the most crucial risk factors for financial institutions. Among these "Credit risk" is the critical component for any institution; banking or non-banking. In general terms credit risk arises when a borrower fails to pay back the lender upon pre-agreed terms. Basel Committee on Banking Supervision defines Credit risk as the "potential a bank borrower or a counterparty will fail to meet its obligations in accordance with agreed terms". The risk arises with the loss of principal or financial reward to the institution due to default. The default arises when the obligor is unlikely to pay its credit obligations or past due more than 90 days on any material credit obligation (Bank for International Settlements, *BIS*). It creates cash flow problems and affects liquidity position of the institution since the institution will fail to recover the loans lent out to customers. Consequently, the credit risk is capable of putting the banks into distress if not adequately managed. And usually the potential for default arises when the borrower expects to cover current obligations from future uncertain cash flows. Hence this exposure to credit risk is the most pervasive source of problems for banks worldwide as a key component of their portfolios is covered by lending. As of the Basel Committee (1999), loans are the largest and most apparent source among these which has a high vulnerability to credit risk for financial institutions. Therefore, understanding the causes of default is crucial to properly manage the portfolios and to set capital structures.

The factors to affect the credit risk are twofold as "Factors influencing systemic credit risk" and "Factors affecting the unsystematic credit risk". Systematic risk is the risk generated by variability in macroeconomic factors including economic, political, factors affecting financial markets (Ahmad & Ariff, 2007). Specifically, systematic risks could be identified as inflationary, interest rate, market, operational, political risk and exchange rate risks. Inflationary risk is the uncertainty in expected returns from investments against inflation. Interest rate risk emanates from increase in market interest rates whereas Exchange rate risk occurs with changes resulting from variation in exchange rate. Political risk arises due to the changes in political conditions whereas Operational risk emanates from failures in internal processes. Market risk is the overall risk of loss resulting from variations in the financial asset values. Market risk is outside the control of investors and has a bearing from interest rate risk, operational risk and exchange rate risk (Yurdakul, 2013). Unsystematic component of credit risk arises from the factors that are firm specific or industry specific (Ahmad & Ariff, 2007). Factors linked with organizational management, individual personalities, consumer preferences, technological developments which are specific to the firm or to the industry in which the firm is operating, are few of the key unsystematic factors that giving rise to credit risk.

In efforts to identify the factors influencing systemic component of credit risk, many empirical studies have attempted to map the association of credit risk and macroeconomic variables as systematic credit risk mainly stems from economy-wide developments. The strong link between systemic credit risk and macroeconomic variables is strongly supported by these empirical literatures However, the magnitude of macroeconomic factors in explaining systematic credit risk differ across industries and sectors (Espinoza & Prasad, 2010).

Figlewski et al (2012), affirm that there are three types of macroeconomic factors that influence a the creditworthiness of an institution as factors relating to general economic conditions, factors characterizing real economy and factors reflecting financial market conditions. Unemployment, inflation etc are the indicators of general economic conditions while Real GDP growth, the change in consumer sentiment are recognized as factors related to the real economy and its future direction. The other group is the financial market indicators which includes interest rates, stock market returns etc. those characterize the behavior of the as financial markets.

2.2 Quantitative Credit Risk Models

Various models have been developed in literature to model the macroeconomic factors into credit risk and Merton (1974) and Wilson (1997) are the most known for development of macro credit models for stress testing (Tian & Yang, 2011). In his model Merton link asset price changes to default probability evaluation. Credit Portfolio View (CPV) model introduced by Thomas Wilson (1997a) within *Mckinsey* is commonly used approach to model credit risks using macro variables (Allen & Saunders, 2002). The basic argument in Wilson's CPV approach is that default and migration probabilities are not independent of the business cycles and it is suitable for macro stress testing as it explicitly models credit risk. The model assesses the relationship between macroeconomic variables and default probability byway of transforming default probabilities as a logistic function of a sector specific index. Then it simulates default probability value under macroeconomic fluctuations and model for future default probabilities to estimate the expected abnormal losses on asset portfolio. The CPV approach has had a significant impact on the macro econometric models that were developed afterward for credit risk stress testing (Kucukkocaoglu & Altintas, 2016). Accordingly, the model links default probabilities to some variables that reflect macroeconomic development to assess the credit risk. However, the focus of the CPV model is portfolio segments rather than individual obligators.

Due to its perfect fit the CPV, is adapted in different ways in credit risk stress testing purposes (Kucukkocaoglu & Altintas, 2016). Boss (2002) used CPV to assess the risk exposure of banking system in Austria using Univariate Regression Method. Gross Domestic product (GDP), inflation rate, nominal short-term interest rates, stock index (Australian Traded Index) and oil prices are found to be the best fitted variables capable of explaining credit risk in his model. Virolainen (2004) has used CPV model on the Finland corporate sector to model the industry specific corporate sector bankruptcies from 1986 to 2003. The findings show a noteworthy relationship between corporate sector default rates to GDP, interest rates and corporate indebtedness. Inspired by CPV approach Kucukkocaoglu & Altintas (2016), developed a risk model with LSM to estimate credit loss distributions of the

Banking System in Turkey. Their model confirms a strong statistical association of systemic component of credit risk and macroeconomic factors namely, GDP, Nominal Interest Rates, exchange Rate and Inflation. Their findings show a strong negative relationship between NPL ratios and GDP and weak positive relationship with Interest Rates which turns to be negative in the first lag. Further, Kucukozmen & Yuksel (2006) used CPV approach to model the Turkish banking loan portfolios, through autoregressive integrated moving average (ARIMA) structures. Their estimations show that variations in NPL ratios can be explained by macroeconomic variables including gross national product (GNP), exchange rate, interest rate, current account balance, unemployment rate, consumer price index, industrial production index, total domestic loans of the banking system, money supply and capital market index.

Sorge & Virolainen (2006) also adapted the CPV for a macro stress test on default probability in Finlands' corporate sector. Their model measures the crucial involvement of measures of profitability, indebtedness and interest rates with key explanatory macro variables such as GDP, the nominal annual interest rate and corporate indebtedness. The results indicate a noteworthy association between sector specific default rates with GDP & interest rates. Impact of GDP is found to be more significant and persistent than the interest rates. A framework was developed by Wong et al. (2008) to stress-test the credit exposures of Hong Kong's retail banks to macroeconomic shocks in which they revealed a strong correlation between the default rates and economic variables, like Hong Kong's GDP, Mainland's GDP, Interest rates and property prices. In a study by Otani et al (2009) the CPV approach is used with a Vector Autoregressive (VAR) estimation to model the variables of GDP, consumer price index, overnight call rate, nominal exchange rate and outstanding amount of bank lending to credit risk. The study has employed the same framework used by the Bank of Japan (BOJ) in credit risk stress testing.

Pesaran et al (2003) use a Global VAR (GVAR) model to assess the relationship between macroeconomic variables and default probabilities. In this study GDP, nominal interest rates, exchange rates, money supply, consumer prices and equity prices, from 1979-1999 are used as explanatory variables. Kattai (2010) adapted VAR to develop a model for credit risk analysis of the Estonian Banking Sector. As per the findings of the study economic growth, inflation, unemployment, interest rates, indebtedness and credit growth are the macro indicators that matter default probabilities most. GDP growth and interest rate are identified to be the leading factors among these while any shock to the base interest rate would take about a lag of one year to fully transmit into default probabilities. In Dovi et al (2009), a VAR model based on CPV approach is adapted in the French manufacturing sector to estimate a macroeconomic model for credit risk stress testing. Yet another study that employs VAR based approach is by Oanh et al (2018) which attempt to develop a stress testing framework for Vietnamian commercial banks. Using a VAR model it estimates the relationship between Real GDP, Interest Rates, Lending rate and Real Effective Exchange rate to credit risk measured in terms of nonperforming loans.

Alves (2004) developed a co-integrated VAR (CVAR), with expected default frequencies (EDFs) of corporate sector, three-month interest rate, twelve-month change in industrial output, twelve-month change in stock market index and oil price, and Sommar & Hovick (2008), employed a vector error correction (VECM) model in his attempt to study the long-term association between expected default frequency and the factors of the macroeconomy. Explanatory variables fitted into the model are CPI, short term interest rate and industry production. As per his findings interest rate has the strongest impact on expected default frequency among the other factors of interest. Adebola et al. (2011), applied a study to Islamic banks in Malaysia to assess the factors that explain the NPLs using an Auto-Regressive Distributed Lag (ARDL) model. Macroeconomic variables considered included the industrial production index, production prices index and interest rate. As of the findings there is a long-term relationship between variables of interest and default rates. Interest rate is found to have a noteworthy positive long-term impact on bad loans while producer prices having a negative impact.

Messai & Jouini (2013), made an attempt to identify the macro and micro level determinants of nonperforming loans in the three countries of Italy, Greece and

Spain. GDP growth, real interest rate and unemployment rate were used in their model in addition to the banks specific variables and the findings show that problem loans are negatively related to GDP growth while there is a positive association between unemployment and real interest rates. Yet another attempt was made by Kearns (2004) to model the loan loss provisioning ratio in the Irish Banking system by employing few macro-financial variables. The selected variables were GDP, unemployment rate, bank earnings, share of loans in total assets, ratio of capital to total assets and growth in loan stock. Rinaldi & Sanchis (2006), provides empirical evidence through their study that disposable income, monetary conditions and unemployment rate are of great influence on household NPLs. Eichengreen & Rose (1998) analyzed the relationship between banking crises using macroeconomic and financial panel data for a group of developing countries which showed a strong association of high interest rates to banking crises of developing countries.

In a study, Klomp (2010) concludes negative GDP growth, high real interest rate and high credit growth, as the most important determinants to cause a banking crisis. Klomp, further highlights that no variable has an impact of more than 60% as the determinants differ between systemic and non-systemic crises and across stages of economic development. Credit risk in commercial and savings banks of Spain was examined by Salas & Saurina (2002) examined by use of panel data during 1985-1997. The study used macroeconomic and individual bank-level variables and based on the findings GDP growth has significant explanatory power. Adding to this, Jimenez & Saurina (2006) presented evidence to explain NPL ratio by GDP growth, credit conditions and real interest rates in the Spanish Banking system. In an attempt to identify the factors contributing to defaults in the Guyanese banking sector, Khemraj & Pasha (2016) has concluded that GDP growth relates with NPL negatively. Further through the study they have disclosed a positive effect of real effective exchange rate (REER) on impaired loans in the Guyanese banking sector.

Yudarkul (2013) has made an attempt in modeling credit risk for banks in which he has identified the credit risk to have a positive relationship with inflation, interest rate, exchange rate, unemployment rate and money supply. Increases in these factors are found to lead to an increase in credit risk. Wong et al. (2008), showed that growth in GDP, rising inflation, growth in money supply relative to foreign reserves, deteriorations in the creditworthiness of institutions &asset price gaps, particularly as foremost indicators of banking distress. Further, they highlight the fact that distress in other economies in the region having a link on determining the probability of banking distress. Vogiazas & Nikolaidu (2011) assessed the NPL determinant in the Romanian banking sector from 2001-2010. In the results they have found that unemployment, inflation rate, construction and investment expenditure, money supply and external debt to GDP as main determinants of NPLs.

Akinlo & Emmanuel (2014) in their study to understand the determinants of non-performing and default loans in the banking system of Nigeria found that economic growth is negatively related to nonperforming loans. They also claimed that credit to the private sector, unemployment and exchange rate having a positive relationship with credit defaults. Beck.et.al (2015) in their attempt to identify the determinants of NPLs in 75 advanced and emerging economies showed that real GDP, nominal effective exchange rate, share price and bank lending rate has significant association to NPL. They further highlight that direction of the impact of exchange rates is decided by the level of foreign exchange lending to unhedged borrowers. Ouhibi.S & Amami.S. (2015) found that NPLs are determined by macroeconomic factors of nominal exchange rate, consumer price index, gross capital formation, GDP, FDI, exports and unemployment.

Louzis et al. (2010) has attempted to find the causes of default in the Greek banking system through panel data analysis of 9 largest Greek banks. The findings show that impaired loan volumes are significantly connected to macroeconomic variables of GDP, unemployment, interest rate and quality of management. The growth in real GDP is found to have the strongest long term effect on the non - performing business loans are found to be sensitive to lagged unemployment affects with one lag. Mohammadreza & Muhammad (2013) has tried to evaluate the cyclical sensitivity of loan quality in the commercial banks in Malaysiain which they have found interest rates and net FDI outflow as the most effective factors on NPL. The factors are found to have a simultaneous positive effect and a reverse effect with one-year lag. In an attempt to identify the bearing of macroeconomic and internal factors on banking distress banking sector of Indonesia, Wulandari et al. (2017) identify that economic growth is negatively significant for predicting banking distress while inflation, interest rate, exchange rate and liquidity do not significantly affect the banking distress in Indonesia.

The Gross Domestic Product (GDP) growth is one of the key macro determinants identified in explaining default risk in many of the studies. Higher GDP growth is said to have a negative association with NPA as GDP can significantly influence the repayment capacity of borrowers (Thiagarajan et al. 2011). As Davis & Karim (2008) state, growth in GDP will not only reduce loans going on non-performing, but can also delay banking crises due to pro-cyclicality. Further evidence is given by Vazquez et al (2012) that there is a contrary association among GDP growth and NPLs in the Brazilian Banking sector. As of their findings, GDP growth inversely relates to non-performing loans with the effects operating up to a three quarter lag. Further the outcomes show that there are differences in the persistence of NPLs across credit types. Loan quality is found to be more sensitive to growth in GDP in certain loan categories such as small consumer loans, credit to agriculture etc. Banks with large exposures highly procyclical credit types are suggested to be more vulnerable to significant deterioration in asset quality during economic downturns.

Castro (2012) analyzed the relationship between the economic development and banking credit risk in Greece, Ireland, Portugal, Spain and Italy (GIPSI) using a dynamic panel data approach. Study has concluded that the GDP growth negatively affects credit risk where non-performing loans increase when GDP and share price indices decrease. Further, interest rate, unemployment rate and exchange rate are found to positively affect credit risk. Hippolyte (2005) has examined the causes of NPLs in sub-Saharan Africa during the economic & banking crises in 1990s. The findings show a significant association of NPLs to macroeconomic variables namely economic growth, real interest rate, net interest margin, real exchange rate& interbank loans. Lobna et al (2014) has also tried to identify the causes of household

NPLs in the banking sector of Tunisia. Dynamic panel data analysis used from 2003 until 2013 for 16 Tunisian banks show that NPLs are affected by real GDP growth rate, lending rate &inflation rate. However, given the limited availability of historical default rates most of these studies have employed accounting based non-performing or loan loss ratios as dependent variables in investigating the influence of the macroeconomic variables on NPLs.

An attempt was made by Badar and Javid (2013) to assess the impact of macroeconomic factors on nonperforming loans of Pakistani Commercial Banks by way of VECM model. Their findings show that there is a long run association of nonperforming loans with money supply and interest rates. Additionally, they have observed a weak short run dynamic between NPLs, inflation and exchange rate. Dash & Kabras' (2010) studied determinants of NPLs in India through regression analysis. The macroeconomic variables namely real GDP, inflation & real effective exchange rate and bank specific variables namely real bank size, interest rate, annual loan growth &loans to total assets ratio were used by them in the analysis. Their findings indicate a strong negative relationship between NPL and real GDP growth and a strong positive relationship among NPL and REER.

Foglia (2009) reviewed the quantitative methods developed at regulatory authorities, particularly by the Central Banks for credit risk stress testing purposes. The Bank of England uses Linear OLS to model short term interest rates, GDP growth, and equity return to logit transformed aggregate default rates. In Bank of Canada, Credit to GDP, GDP growth, Medium-term business loans rate and Unemployment rate are employed as independent variables in the credit risk model. Bank of Italy uses VAR approach to link inflation, interest rate, corporate default rate, output gap and real exchange rate. Logit transformed Loan Loss Provision (LLP) is linked to real GDP growth, credit growth and variation in short-term interest rate and its own lag through dynamic panel data estimation Deutsche Bundesbank. European Central Banks' Credit risk modeling approach includes estimation of regression model to link the Expected Default rates of euro area corporate to macroeconomic factors namely Euro-area real GDP, short-term interest rate, inflation, Real equity prices and exchange rate. Further, Swiss National Bank uses static and dynamic panel estimations in credit risk modeling. These models feed Logit transformed LLP ratios as the dependent variable and GDP growth, level of three-month Interest Rate, unemployment rate, corporate bond spread and Bank control variables as independent variables.

Among the few studies conducted in Sri Lanka to identify the relationship between credit risk and macroeconomic variables, Ekanayake & Azeez (2015) has attempted to identify the determinants of NPLs in the Licensed Commercial Banks (LCBs) sector. A panel data regression has been used to analyze determinants of credit risk of nine domestic LCBs with data from 1999-2012. GDP, Inflation, lending rates and unemployment are the macroeconomic determinants employed in the model. As of the findings of their study GDP, inflation, and average prime lending ratio have a noteworthy impact on determining the NPL ratio in commercial banks. GDP and inflation show a negative impact while lending rate is shown to have a positive relationship with NPLs.

Kumarasinghe (2017) has employed an OLS regression analysis to capture the relationship of default rates to macroeconomic variables in the banking sector. Seven explanatory variables namely, GDP, Unemployment, Inflation, Interest Rate, Exchange Rate, Exports Growth and Capital market growth are used as explanatory variables and as of the findings only export growth and GDP are significant in determining the NPLs.

With reference to all these literature it is clearly evident that there is a causal relationship between macroeconomic variables &banking sector default rates. Accordingly, the framework of this particular study has been developed being in line with the findings summarized in this chapter.

CHAPTER 3

METHODOLOGY

3.1 The Conceptual Framework of Credit Risk Modeling

Martin Cihak (2007) has presented a framework for the Macroeconomic Stress Testing of credit portfolios as illustrated in Figure 3.1. As per his explanation stress events are linked to external shocks which could be explained by macroeconomic models. Macroeconomic models can define the linkages among macroeconomic variables such as GDP, Interest Rate, Exchange Rate etc to external shocks. However, this group of models does not capture the relationship among macroeconomic variables and financial variables, mainly asset quality. Hence a "satellite credit risk model" is rooted in to the framework to map the macroeconomic variables into asset quality. Satellite Credit Risk models link bank specific risk variables mainly the asset quality to macroeconomic variables and explain asset quality as a function of individual bank variables and system wide macroeconomic variables. Consequently, the macroeconomic model together with the satellite credit risk model can map assumed external shocks into bank-by-bank asset quality shocks.

Based upon this explanation by Cihak (2007), the study focused on the second type of models, which are satellite credit risk models that link macroeconomic variables to asset quality. Valid stress testing requires a comprehensive satellite risk models with high predictive power to preserves the known economic relationships. Hence, the study attempted to develop a best fitted satellite credit risk model to link the banking sector asset quality to macroeconomic variables in Sri Lanka.

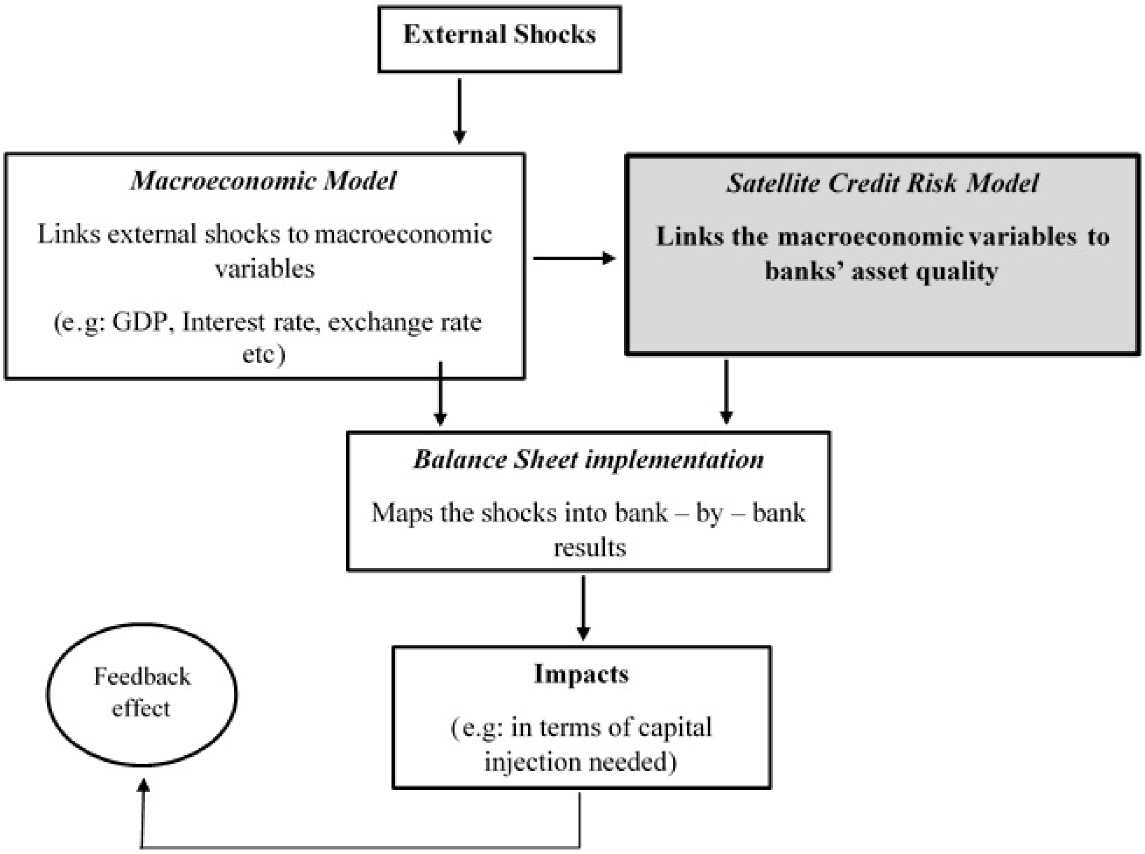


Figure 3.1: General Stress Testing Framework
Source: Cihak (2007)

As discussed in Chapter 2, Credit Portfolio View approach (CPV) developed by Thomas Wilson within Mckinsey, is the most widely used approach in literature to model banks' credit risk by way of a satellite credit risk model. With careful inquiry into empirical literature, the same CPV approach was adapted in this study as well to model credit risk in the Sri Lankan banking sector employing macroeconomic variables.

3.1.1 Credit portfolio view (CPV) model

The CPV model links default and credit quality migrations to macroeconomic factors upon the argument that default and migration probabilities are not independent of the business cycle. The default rates are modeled in the logistic functional form to confirm that the values are in the range of [0,1] and the relationship with macro variables are nonlinear.

Given that $p_{j,t}$ is the default rate in sector j at time t and $y_{j,t}$ is the sector specific macroeconomic index,

$$p_{j,t} = \frac{1}{1+\exp(y_{j,t})} \text{ ----------------------------------- } (3.1)$$

$y_{j,t}$ is the sector specific macroeconomic index derived using multiple time series model that contemplates a number of macroeconomic variables. $p_{j,t}$ varies between 0 to 1 representing the probability of default in the selected sector.

The sector specific macroeconomic index could be denoted as;

$$y_{j,t} = \ln\left(\frac{1- p_{j,t}}{p_{j,t}}\right) \text{------------------------------- } (3.2)$$

The transformed macroeconomic index is then determined by a group of selected macroeconomic variables to find the link between the default rates and the macroeconomic factors.

$$Y_{j,t} = \beta_{j,0} + \beta_{j,1} X_{1,t} + \beta_{j,2} X_{2,t} + \ldots \ldots \ldots \ldots \ldots \ldots + \beta_{j,n} X_{n,t} + \upsilon_{j,t} \text{ --------}(3.3)$$

where β_j is the set of regression coefficients to be estimated for the j th industry, $X_{1,t}$ (i = 1, 2,…, n) is the set of explanatory macroeconomic variables and $\upsilon_{j,t}$ is a random error term that is assumed to be independent and identically normally distributed.

Accordingly, equation 3.3 defines the relationship between transformed sector specific index and identified macroeconomic variables. Consequently, the relationship between default rates/ NPLs and macroeconomic factors can be defined through equation 3.2 above. As preferred in Otaniet al. (2009), the coefficients of β_j in equation 3.3, are estimated through a Vector Error Correction Model (VECM).

3.1.2 Vector Error Correction Model (VECM)

Vector Autoregressive (VAR) is a form of system equations used in multivariate time series analysis to explain variables by its own lags and current and past lags of other variables. However, VAR is applied only when the variables are stationary in nature. Accordingly, if the variables are non-stationary and co-integrates the VAR is used in the form of an Error Correction Model to capture the relationships. VECM estimates the level to which a variable can be brought back to equilibrium condition after a shock on other variables.

Let y_i = ($y_{1i,}$ y_{2i}, y_{3i}, ……………….. y_{ki})’ denote an (n x 1) vector of stochastic time. A VAR model of order p i.e. VAR (p) can be interpreted as;

$$y_t = c_1 + A_1 y_{t-1} + A_2 y_{t-2} + \text{-------} + A_P y_{t-P} + \varepsilon_1 \quad , t = 1, 2, \ldots\ldots, T \quad \text{---------} (3.4)$$

With cointegration transformation,

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_1 \quad \text{--}(3.5)$$

where

$$\Pi = \sum_{i=1}^{p} A_i - \text{I and } \Gamma_i = \sum_{j=i+1}^{p} A_j$$

If y_t has a cointegration relationship which is further explained in the below section in this Chapter, then Πy_{t-1} ~ I(0) and accordingly equation 3.5 can be rewritten as;

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_1 \quad \text{--}(3.6)$$

where $\beta' y_{t-1} = ecm_{t-1}$ is the error correction term that reflects long term equilibrium relationships between variables. Accordingly, equation 3.6 denotes the general equation of a Vector Error Correction (VECM) model. The Error Correction Models connects the long-run equilibrium relationship as reflected by cointegration to the shortrun dynamics which denotes how the variables react when they move out of long-run equilibrium.

3.1.2.1 Concept of stationarity

Stationarity is the most fundamental and vital statistical property in stochastic time series analysis, as most time series models require the underlying generating processes to be stationary. Nevertheless, time series analysis does not confine to analysis of stationary processes. Non-stationary series could be directly used in models like Vector Error Correction (VECM) subjected to that the variables are co-integrated.

A series or a process is said to be stationary if the properties of mean, variance and autocorrelation does not change over time.

1. Mean of the series μ is constant for all t

$$E(X_t) = \mu\ (t)$$

2. Variance of the series σ^2 is constant for all t

$$Var\ (X_t) = \sigma^2\ (t)$$

3. Autocovariance of the series depends only on the lag value k

$$cov\ (X_{t1}, X_{t2}) = \gamma(t_1, t_2)$$

A non-stationary series could be made stationary through differencing. If X_t is a process integrated of order d, denoted by I (d), it can be rendered by differencing the series d times. That is ifx_t is non-stationary $(x_t - x_{t-1})^d$ is stationary. Non - stationarity of a time series is confirmed by way of existence of a unit root.

Among the many validation tests used to confirm the existence of unit root, Augmented Dickey–Fuller test and Phillips–Perron test are the most commonly used in research. ADF test the existence of unit root under the null hypothesis that a unit root is present in a time series sample. Accordingly, ADF test was employed in identifying the stationarity condition of variables in the study.

3.1.2.2 Co-integration

Co –integration is a statistical property of time series variables which assesses the mutual association between variables. If there is a stationary linear combination of nonstationary random variables, the variables combined are said to be cointegrated. That is if y_t is an n x 1 vector of I(1) time series, y_t is cointegrated if there exists an n x 1 vector β such that

$$\beta' y_t = \beta_1 y_{1t} + \ldots\ldots\ldots\ldots\ldots + \beta_n y_{nt} \sim I(0) \text{ ----------------------------(3.7)}$$

3.1.2.3 Granger causality

Granger Causality is a statistical concept useful for identifying whether one-time series is useful for forecasting of another time series. As Autoregressive models describe the joint generation process of a number of variables overtime, understanding the causality between the variables is important.

If X and Y are two random variables, X is said to granger causes Y, if Y can be explained in terms of lag values of X and lag values of Y.

$$Y_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots\ldots\ldots + \alpha_p X_{t-p} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_p Y_{t-p} + e_t'$$

$$Y_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{p} \beta_i Y_{t-i} + e_t' \text{ ------------------------------------ (3.8)}$$

Similarly, Y is said to granger causes X, if X can be explained in terms of lag values of X and lag values of Y.

$$Y_t = \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \ldots\ldots\ldots + \gamma_p X_{t-p} + \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + \delta_p Y_{t-p} + e_t'$$

$$X_t = \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + e_t'$$

The causality between two variables can be unidirectional, bidirectional or no causality.

3.2 Data Collection and Analysis

3.2.1 Selection of model variables

As discussed, the research framework for this particular study has been developed with careful review into empirical literature. Accordingly, the variable selection was done being in line with these published literature. Given the non-availability of accurate historical default rates in the public domain, non-performing loans ratio (NPL) is used as the proxy for default rates in this study as well. NPL ratio is the portion of gross non-performing loans to total loans.

$$\text{NPL Ratio} = \frac{\text{Nonperforming Loans}}{\text{Total Loans}}$$

As of the classification by Central Bank of Sri Lanka, loans and advances in arrears for 90-180 days are classified as “Non-performing”, 181 - 360 days as “Sub Standard”, 361 - 540 days as “Doubtful” and over 540 days as “Loss”. The non-performing loans portfolio considered in calculating the NPL ratio is the total of all these four categories which reflect the loans & advances overdue for 90 days or more net of interest suspense. These NPL Ratios are then converted to sector specific macroeconomic index through equation 3.2 given above. Then this converted index is fitted into the model with other selected variables.

In an attempt to identify determinants of NPLs in Sri Lankan commercial banks Ekanayake &Azeez (2015) employed four macroeconomic variables namely real GDP growth, Inflation, Unemployment & Average Prime lending ratio. Kumarasinghe (2017) used GDP, Inflation, Interest Rate, Unemployment, Exchange Rate, Exports Growth and Capital Market Growth as exogenous determinants of credit risk. Analyzing the findings of these studies and other literature presented in chapter 2, following variables are used in the model definition in this study. As suggested by Figlewski (2012), three variables were identified under the two groups of factors relating to general economic conditions and factors characterizing real economy. Accordingly, following exogenous variables were selected to represent the macroeconomic condition.

Table 3.1: Selected variables for VECM estimation

Factors relating to general economic conditions	• Unemployment • Exchange rate
Factors characterizing real economy	• Real GDP

I. Unemployment

Unemployment is used as another indicator of general economy as it is expected that unemployment has an influence over repayment capacity of borrowers. Accordingly, Unemployment rate which is the proportion of unemployed population to the total labour force was selected as an exogenous.

II. Exchange Rate

Exchange Rate was selected to reflect the external competitiveness of local currency. Real Effective Exchange Rate (REER) was used to capture the movement in exchange rate over the study period. REER is the weighted average of the country's currency relative to a basket of other major currencies adjusted for the effects of inflation is used as the proxy for exchange rate.

III. Real GDP

Real GDP was used as another macroeconomic variable to capture the movement of real economy in the model. Accordingly, the real GDP growth with base year 2010 was selected for the purpose. Real GDP is the sum of value added in an economy during a given period, adjusted for the effect of inflation.

These three variables along with NPL were fitted as exogenous variables to a VECM model to identify the relationships.

Data for the model was used on Quarterly frequency from 2009 quarter 1(Q1) to 2018 quarter 4 (Q4). Data collection was done from secondary data sources available in the public domain. Data were mainly obtained from statistical publications of the Central Bank of Sri Lanka and the Department of Census and Statistics including the Annual Reports. It was observed that there were no significant structural breaks during the period under consideration. Additionally, there were no missing data points in the selected data series. Accordingly, the data were directly used in the model fitting exercise.

3.2.2 Data Processing and Analysis

Selected variables were fitted to a VECM model expecting to take following signs (**Table 3.2**) corresponding to the movement of NPL, based on the findings of empirical research. Accordingly, real GDP growth is expected to have a negative association with NPL while other variables are expected to be positively related to NPL.

Table 3.2: Definitions and expected signs of the variables

Variable	Definition	Expected sign
$\mathbf{GDP_t}$	Growth rate in Gross Domestic product at time t	-
$\mathbf{UNEMP_t}$	Unemployment at time t	+
$\mathbf{EXRT_t}$	Real Effective Exchange Rate at time t	+

However, since the focus of the study is to understand the determinants of NPLs, only the equation of NPLs will be studied among the other system equations in the analysis.

The Data could directly be filtered to the model since there were no significant structural break and missing data points. The model fitting exercise was done using E-Views software version 6. E-Views is one of the most commonly used software for quick and efficient econometric and statistical analysis. Hence E-Views was preferred among the other software for the analysis. The following chapter 4 on analysis discusses in detail the relationships discovered among the study variables.

CHAPTER 4

ANALYSIS

4.1 Data Analysis and Interpretation

As discussed in Chapter 3, with careful review into literature, three macroeconomic variables along with NPL ratio were identified to fit the model. The selected variables are namely the NPL Ratio (NPL), Real GDP growth rate (GDP), unemployment rate (UNEMP) and Exchange Rate (EXRT). For a detail understanding on the basic statistical properties of these variables, the descriptive statistics are given in Table 4.1 below.

Table 4.1: Descriptive Statistics of selected variables

	NPL	GDP	UNEMP	EXRT
Maximum	8.8	16.1	6.2	111.3
Minimum	2.5	0.5	3.9	94.2
Std. Dev.	1.8	2.1	0.6	4.3
Skewness	0.8	-0.4	1.4	0.2
Kurtosis	2.7	1.9	4.3	2.4

These statistics express the behavior of variables over the selected 10-year period from 200 – 2018. The highest NPL recorded during the period under consideration has been 8.8% whereas the lowest was 2.5%. The highest NPL was recorded in 2009 indicating that the banks have failed to collect 8.8% of every loan lent to borrowers in their loan portfolios. Average GDP growth rate over the 10 year period has been 5.8% with the recorded highest of 8.6%. Unemployment data has the lowest standard deviation indicating that the unemployment has remained more or less stagnant throughout the period under consideration with a minimal variation. The highest Average exchange rate represented by Real Effective Exchange Rate adjusted for inflation is reported as102.3 during the period. Unemployment has the lowest standard deviation among the data set while Exchange Rate data has the highest.

Data plots at Figures 4.1 to 4.4 presented below helps to further understand the dynamics in data series.

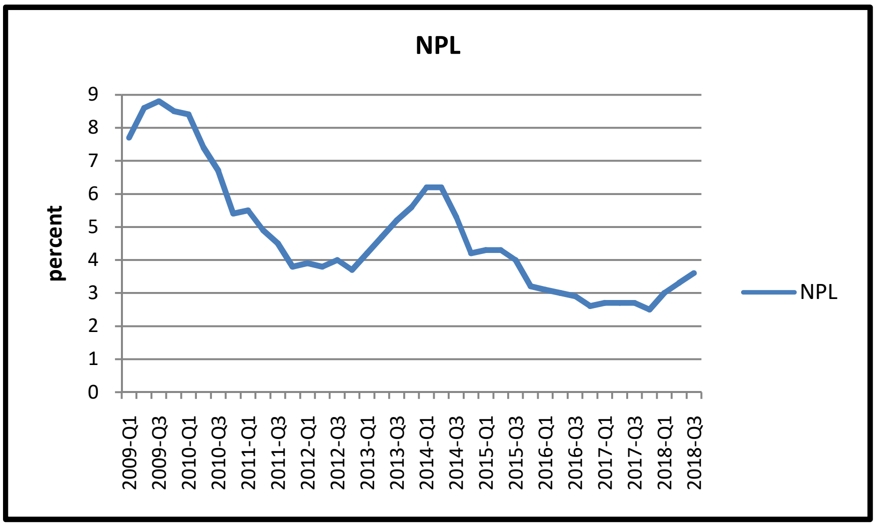


Figure 4.1: Data plot of Non- performing loans (NPL)

NPLs are observed to be on a decreasing trend during the period under consideration. However, a growth trend can be seen since later part of 2017. The highest NPL ratios were recorded in 2009 – 2010 mainly on the account of second round effects of the global economic recession. Another hike in NPLs is seen during late 2013 and early 2014, mainly due to the weaker quality of loans in the pawning portfolio. However, it is clearly observable that the NPLs are on a growing trend since late 2018, which has become a key concern for financial institutions at present as well. GDP growth has been volatile over the 10 year horizon with the highest growth recorded in Q1, 2012. A noteworthy drop is visible in GDP growth during the recent years. Unemployment ratio is observed to have declined over the years and stagnant at around 4% with a positive reflection on the economy.

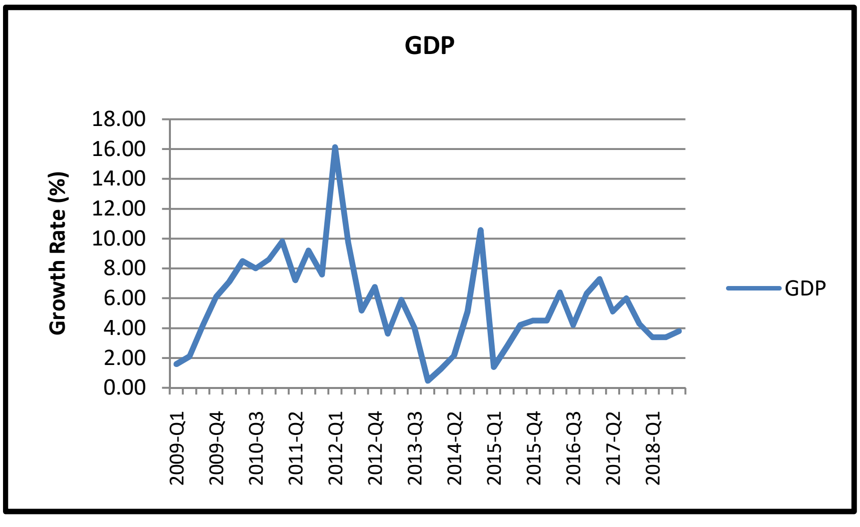


Figure 4.2: Data plot of Real GDP (GDP)

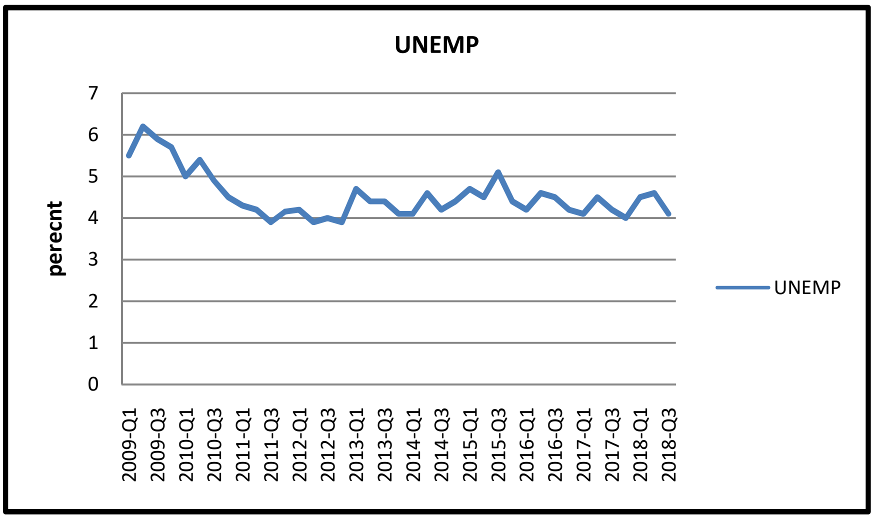
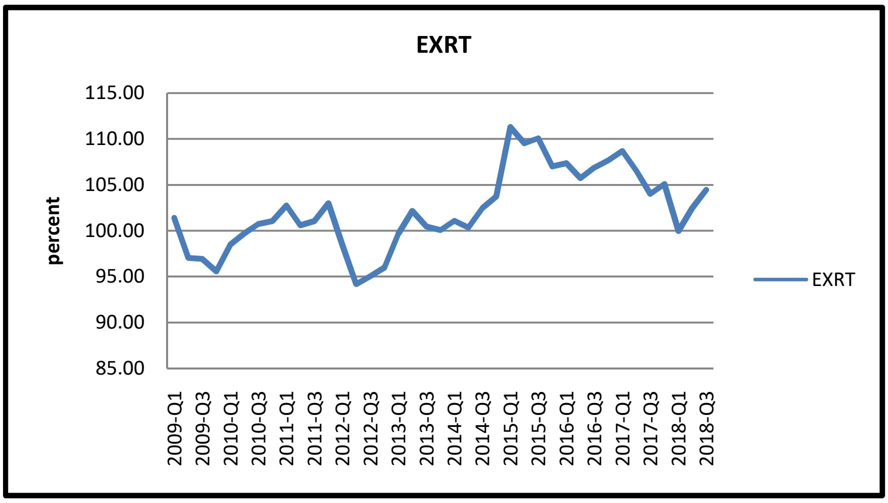


Figure 4.3: Data plot of Unemployment (UNEMP)



]**Figure 4.4 : Data plot of Exchange Rate (EXRT)**

Upon understanding the basic statistical properties of data, the NPL ratio was converted into the sector specific index. The conversion was done through 3.2 presented in Chapter 3. As of the plots certain variables are observed to be non-stationary as a trend can be seen in the data plots. Accordingly, the stationarity of data were confirmed through ADF test before they were fitted into the model. The ADF Test results are discussed in detail under the following section.

4.1.1 Test of stationarity

ADF test checks the null hypothesis that a unit root is present in the time series sample. Accordingly, Table 4.2 summarizes the ADF Test results for selected model variables.

Table 4.2: ADF Unit Root test results

	At level		At first difference	
	Test Statistic	P value	Test Statistic	P value
NPL	-1.7739	0.3863	-4.0778	0.0038
GDP	-2.2212	0.2024	-7.5038	0.0000
UNEMP	-2.5054	0.1222	-5.8539	0.0000
EXRT	-1.7884	0.3804	-6.3048	0.0000

As of the test statistics NPL, GDP growth, Unemployment and Exchange Rate are found to be non-stationary at the level as the test hypothesis is accepted at 5% significance level. Further, the ADF test confirms the variables to be stationary at I(1). Accordingly the data confirms the basic requirement to employ an error correction model for the analysis. Subsequent to confirming the non-stationarity condition of data, the co-integration test was done to check on the existence of cointegration between variables.

4.1.2 Test of Co-integration

Subsequent to confirming the non-stationarity of data, co-integration test was done to get a confirmation on the existence of cointegartion between the variables under consideration. The Johansen cointegration test output is given in Table 4.3 below.

Table 4.3 : The Johansen cointegration test output

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.477389	58.0994	47.85613	0.0041
At most 1 *	0.448971	34.08942	29.79707	0.0151
At most 2	0.238004	12.03859	15.49471	0.1551
At most 3	0.052144	1.981465	3.841466	0.1592
Trace test indicates 2 cointegrating eqn(s) at the 0.05 level				

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.477389	24.00998	27.58434	0.1344
At most 1 *	0.448971	22.05083	21.13162	0.0371
At most 2	0.238004	10.05713	14.2646	0.2082
At most 3	0.052144	1.981465	3.841466	0.1592
Max-eigenvalue test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

As of the test results the null hypothesis of "There is no cointegration" is rejected at 5% level of significance. The test results indicate that there are at least three cointegrating relationships between the selected variables of GDP, UNEMP, EXRT and NPL. Accordingly there is a long run mutual association between the variables under consideration which is mandatory requirement for an ECM.

4.1.3 Model specification

As the statistical tests confirm the non-stationarity of selected variables at level and the existence of conitegration relationship between the variables, a VECM model which is deemed as most appropriate for the analysis was fitted to identify the relationship between selected model variables. Model equation of the fitted VECM is as follows.

D(NPLR) = C(1)*(NPLR(-1) - 0.415614206331*GDP(-1) -2.04685557526) + C(2)*(UNEMP(-1) + 0.0837387474334*GDP(-1) - 4.98300708095) + C(3)*(EXRT(-1) + 2.33269668801*GDP(-1) - 116.672263132) + C(4)*D(NPLR(-1)) + C(5)*D(NPLR(-2)) + C(6) *D(UNEMP(-1)) + C(7)*D(UNEMP(-2)) + C(8)*D(EXRT(-1)) + C(9) *D(EXRT(-2)) + C(10)*D(GDP(-1)) + C(11)*D(GDP(-2)) + C(12) ---------------------------------- **(4.1)**

The short run dynamics of NPLs can be clearly analyzed through this model. The estimated system of equations of the VECM model is given in Appendix B. Further, Table 4.4 below summarizes the estimated VECM coefficients and its p values for further understanding of the significance of selected variables in the fitted model.

Table 4.4: Estimated VECM coefficients

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.48705	0.155918	-3.12376	0.0024
C(2)	0.825965	0.497072	1.661659	0.0998
C(3)	-0.08011	0.023347	-3.43143	0.0009
C(4)	0.426972	0.183257	2.3299	0.0219
C(5)	0.416866	0.190503	2.188236	0.0311
C(6)	0.72366	0.390304	1.85408	0.0668
C(7)	0.53095	0.253036	2.0983	0.0385
C(8)	0.080261	0.035577	2.255967	0.0263
C(9)	0.063829	0.031446	2.029822	0.0451
C(10)	-0.03011	0.085897	-0.3505	0.7267
C(11)	-0.008618	0.068003	-0.126726	0.8994
C(12)	-0.08282	0.067907	-1.21965	0.2256

The output shows the significance of macroeconomic regressors in explaining the dynamics of NPLs. As of the model output it is observed that Unemployment rate and Exchange rate are significant in explaining the dynamics of NPL. Further, NPL is observed to have a lag effect on its own. Unemployment is observed to have a significant negative bearing on NPLs with a 2 period lag. Also the Exchange rate also seems to have a positive effect on NPL with a lag. Positive relationship between Unemployment and NLPs confirms the empirical findings including Louzis et al. (2010) where he found that unemployment with one-period lag is one of the foremost indicators of NPLs in the Greek financial system. The magnitude of the coefficient is 0.019598 which indicates that the relationship between the unemployment rate and NPLs is not as strong as that between the growth in real GDP growth and credit quality.

Further, a positive co-movement between the NPLs and the real effective exchange rate can be observed in the output. This shows that the international competitiveness on local currency too has a bearing on the repayment capacity of borrowers. However, the model suggests the exchange rate having a 1 and 2 period lagged effect which indicates that the effect of movement in exchange rate requires at least 1 quarter to get transmitted into the system. However, as per the test output a significant short run association cannot be observed between GDP growth and NPLs as expected.

Additionally, the model suggests lagged NPL itself to have a positive relationship on loan quality and borrower repayment behaviour. However, based on the magnitude of coefficients it is clearly observed that the unemployment rate has the most significant explanatory power among the variables other than NPLs.

4.1.4 Pairwise Granger Causality Analysis

Subsequent to confirming the model fit, granger causality was checked with to understand the causal relationships between model variables, if any. Table 4.5 shows the Granger causality test results. The test results indicate unidirectional causal relationships between NPL and GDP and NPL and UNEMP. GDP granger causes with NPL as the null hypothesis "GDP does not Granger Cause NPL" is rejected at 5% level of significance. Upon the same basis, Unemployment is identified to granger causes NPL as the null is rejected upon the p value less than 5 percent. However, Exchange rate cannot be identified to have a causal relationship with NPL. Accordingly, the Granger Causality test confirms GDP and Unemployment to have a causal relationship with NPLs and therefore useful in forecasting NPLs. However, these causal relationships are unidirectional. However, the VECM estimate discussed above doesn't show a significant short run dynamic between GDP and NPL though the granger causality test suggest a unidirectional relationship among the two variables.

Table 4.5: Pairwise Granger Causality Test

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP does not Granger Cause NPL	36	0.94900	0.0043
NPL does not Granger Cause GDP		5.44774	0.4299
UNEMP does not Granger Cause NPL	36	0.62323	0.0113
NPL does not Granger Cause UNEMP		0.32739	0.6057
EXRT does not Granger Cause NPL	36	2.11457	0.1200
NPL does not Granger Cause EXRT		0.88155	0.4621
UNEMP does not Granger Cause EXRT	36	0.01289	0.9980
EXRT does not Granger Cause UNEMP		0.79399	0.5072

GDP does not Granger Cause UNEMP	36	0.43951	0.7265
UNEMP does not Granger Cause GDP		2.68049	0.0653
GDP does not Granger Cause EXRT	36	0.36016	0.7822
EXRT does not Granger Cause GDP		4.41388	0.8055

4.1.5 Impulse Response

An Impulse response function highlights how the system response to an impulse of another variable in the system into the future. The impulse response function was used to trace the response of NPL to exogenous impulses of seven study variables in the fitted model. The interpretation is presented in Figure 4.5 below.

As per the graphs, if a one standard deviation positive shock is given to GDP, the NPL will rise initially until quarter 3 and then will subsequently decline to the negative region until quarter 6. From 4th to the 7th quarter the reaction will be positive. From quarter 7 onwards the NPL would move in the positive region. A shock (innovation) to EXRT would result in NPLs to move to the negative region by quarter 2 onwards.

A positive shock to unemployment would result NPL to react positively from the first quarter itself. By quarter 4 the movement of NPL gets stagnant indicating that the effect of the shock has been permanent.

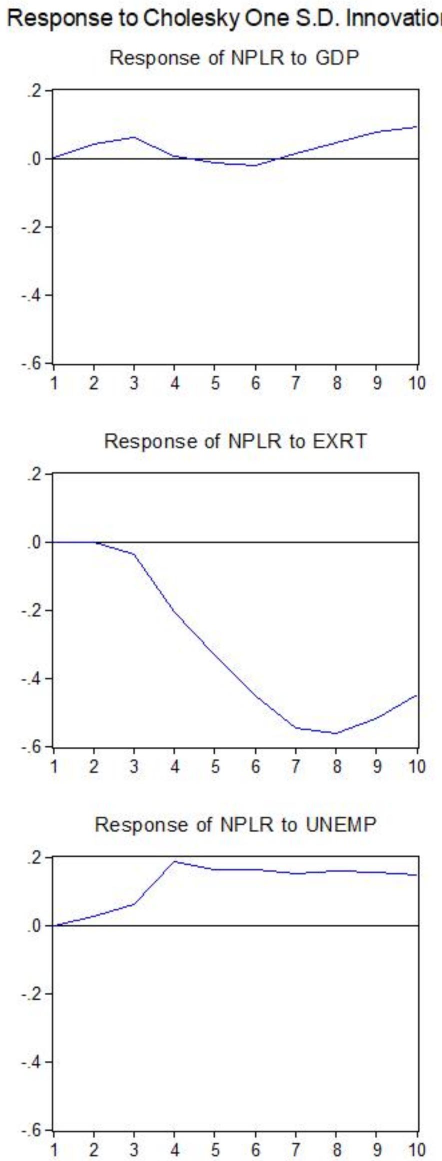


Figure 4.5: Impulse Responses

4.1.6 Variance Decomposition

The variance decomposition show sthe scale of forecast error variance of each of the variables explained by exogenous shocks to the other variables. It helps to determine the magnitude of the error realization coming from unexpected changes in the other variable (Table 4.6)

In the short run, that is in quarter 3, impulse to NPL account for 97.1 percent variation of the fluctuation in NPL. That is fluctuation of NPL is mainly driven by its own shock. In the long run which is quarter 10, EXRT remains to contribute to 67.7 per cent of fluctuation in NPL. Shock to UNEMP can cause 22.4 per cent fluctuation in NPL. Further, a shock to GDP cannot contribute much to a fluctuation in short run nor long run.

Table 4.6: Variance Decomposition of NPL

Period	S.E.	NPLR	GDP	EXRT
1	0.372205	100	0	0
2	0.517088	99.10842	0.6584	0.000365
3	0.63269	97.1814	1.402362	0.351155
4	0.729334	83.30145	1.066458	8.353696
5	0.832914	67.73853	0.846509	22.06181
6	0.965172	51.07591	0.673084	38.40806
7	1.120169	38.0974	0.515751	52.23739
8	1.264681	29.9288	0.542339	60.80207
9	1.377762	25.23097	0.770746	65.41036
10	1.459813	22.47444	1.098317	67.75374

Figure 4.6 further provides a clear graphical representation of this decomposition of variance. That clearly shows the magnitude of the error realization coming from each variable.

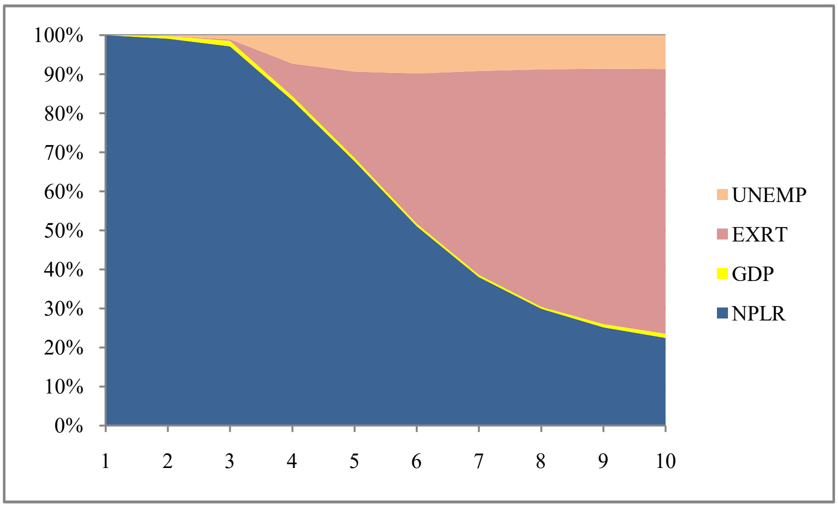


Figure 4.5: Graphical representation of Variance Decomposition of NPL

Given these findings it is understood that Unemployment rate and Exchange Rate are significant determinants of banking sector credit risk in Sri Lanka. Both variables indicate a positive bearing on NPL, which indicates that Non-performing or default loan volumes would increase given an increase in unemployment in the economy or depreciation in local currency which leads to growth of exchange rates. Accordingly, there is a significant association between certain macroeconomic variables and banking sector credit risk in the Sri Lankan context. Further analysis on these findings is given in Chapter 5 below.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Macroeconomic determinants of Non-Performing loans in Sri Lanka

As revealed through the fitted VECM model (equation 9), Unemployment and Exchange rate are significant in explaining the dynamics of NPLs in the banking sector in Sri Lanka.

Unemployment rate having a positive association with NPLs is also in accordance with the findings of empirical research including Louzis et al. (2010) and Rinaldi & Sanchis (2006) where unemployment is understood to be a significant determinant of credit defaults. As per the model estimation unemployment has a lagged association with non-performing loans in the Sri Lankan context. Louzis et al. (2010) suggests lagged unemployment as a principal indicator of NPLs in the consumer loan portfolio. High unemployment can negatively affect the present and future cash flows of households as people will have no employment to generate income. This will increase the debt burden of households and thereby will result in bad debt. In turn, increase in unemployment will decrease production as the effective demand will decline. This will decrease revenue for firms which will affect their ability to meet obligations as agreed. Accordingly, in the periods of low unemployment which indeed a period of economic growth, borrowers (individual and firm level) will have the capacity to service debt obligations upon pre-agreed terms. In turn when the unemployment is high the borrowers will tend to default debt obligations given that they find it difficult to generate cash flows to repay debts. Accordingly, unemployment is yet another significant determinant of credit quality in the Sri Lankan context. However, Ekanayake & Azeez (2015) and Kumarasinghe (2017) have identified unemployment to be insignificant in determining the behavior of non-performing loans.

The other key determinant on credit default found through analysis is the exchange rate with lag 3. Exchange rate has a positive co-movement with non-performing loans further confirming the empirical research findings including Khemraj & Pasha

(2016), Akinlo & Emmanuel (2014) and Beck et. al (2013). Khemraj & Pasha indicates that real effective exchange rate has a strong direct relationship with NPLs whereby decrease in the global effectiveness of the national economy transforms into higher NPLs. Exchange rate is an indicator of relative worth of a domestic currency in terms of another currency.When the domestic price of foreign exchange rate rises or in other words when the local currency depreciates procuring foreign products and services become expensive as their cost would be high. Thus domestic currency would be required to acquire the same amount of foreign goods and services than that was before. This would increase the demand for bank credit as funds are needed to cover the additional expenditure originated from exchange rate depreciation (Ngerebo, 2012).Demand for credit from individuals will also increase as prices of final products will be affected. Subsequently, default rates would increase as individual and firms go through difficulties in servicing their debt. Exchange rate is also found to Granger cause NPL as per the Granger Causality Test findings. Further, the NPL ratio is found to sustain itself via a significant feedback effect.

However a significant association between GDP growth and NPL could not be revealed through this analysis. Theoritically, NPLs would remain lower when economic conditions remain good and favorable. In contrast, NPLs would rise when the economy is in a downturn with stagnated growth prospects. Many empirical findings including Ekanayake & Azeez (2015), Salas & Saurina (2002), Kucukkocaoglu & Altintas (2016), Messai & Jouini (2013), Klomp (2010), Khemraj & Pasha (2016) and Castro (2012) have showed GDP growth to negatively affect NPL. High level of real GDP growth habitually entails a higher level of income. This improves the borrower’s capacity to honour their debt obligations upon agreed terms. However, when there is a slowdown in the economy as mirrored through lower GDP growth, household cash flows get affected. Households will not have sufficient cash flows and hence will tend to priorities expenditure for consumption rather than meeting debt obligations. Additionally, firms will also experience difficulties in generating revenue as the economic activities will slow down. Subsequently, the repayment capacity of firms will also get affected similar to the households. Upon this basis GDP growth has a negative relationship with credit defaults. However, a significant association between these two variables could not be identified in this exercise.

5.2 Policy Implications and Recommendations

The most important conclusion to be derived upon these findings is that banking institutions should focus on the macroeconomic developments when granting loans to customers. As discussed Unemployment and Exchange Rate are the most significant determinants in defining the borrower repayment behavior in Sri Lanka. Thus, the institutions need to focus on these in order to reduce the level of NPLs. Given the relationship of these variables, an adverse slowdown in GDP growth (with positive movement in unemployment) indicates that banks should take precautionary measures to tackle the increased demand for credit expansion during economic downturns. They shall look into the ways and means of allocating credit efficiently having a consideration on credit records and availability and reliability of collateral security of clients. Accordingly, the banking institutions may have the capacity to trim down the incidences of defaults and NPLs. Similarly, upon understanding the determinants of defaults, the banking institutions have to trace their behavior to track the plausible events that can occur in future and to come up with precautions accordingly. It is only through a complete understanding on the movement of macroeconomic variables that these institutions can develop comprehensive strategies for credit risk management.

From the perspective of regulators, these findings can lighten them to develop overall macroeconomic strategies to cope up with plausible stress events in the macro economy. The findings clearly imply that the policy makers have a crucial role to play in economic downturns by implementing countercyclical policy measures, reduce the potential for a momentous build up in NPLs. Hence it is expected that the findings of this study would enable the banking as well as other financial institutions to continue to strengthen their credit risk mitigation measures by having an accurate understanding on what really are the causes of credit risk.

5.3 Avenues for future research

In addition to the encouraging findings produced by the study, there are avenues for future research. The same approach can be extended to capture a wide range of economic developments in to the equation. For the purpose, many other key economic variables can be introduced to the model. Additionally, bank specific variables can also be introduced to capture the firm specific factors of credit risk. This particular study was highly restricted to focus on macroeconomic determinants given the restriction in data. However, the unsystemic component of credit risk can easily be captured in, through bank/ firm specific variables being filtered into the same framework. Further, extending on the same line studies can be undertaken at disaggregated levels to assess the interactions between different types of borrower behavior over different loan types such as consumer loans, commercial loans mortgages etc. The same research approach can be utilized to assess the credit risk determinants in other subsectors such as non-bank financial institutions sector. The factors of interest would differ from the study variables of this study; however the same approach could be employed in such analysis as well.

Though this specific study is limited to the banking sector, the same research approach can be employed to study the credit risk determinants in other subsectors such as non-bank financial institutions sector. Additionally, the outcome of this study can be used in future research in credit risk stress testing. As the study findings identify the key determinants of defaults, the identified variables can be employed in stress testing to analyse the sensitivity to exceptional but plausible shocks. The study can be extended to be used for both micro and macro level stress testing purposes to assess the resilience at individual institutional level as well as the systemic level.

Reference list

Adebola, S., Yusoff.W.S.W., Dahalan,J. (2011). The impact of macroeconomic variables on Islamic banks financing in Malaysia. Research Journal of Finance and Accounting, 2(4), Retrieved from https://www.iiste.org/.

Ahmad, N. H. & Ariff, M. (2007). Multi-country Study of Bank Credit Risk Determinants. International Journal of Banking and Finance, 5(1), 135-152. Retrieved from http://www.ijbf.uum.edu.my/

Akinlo.O.& Emmanuel.M. 2014. Determinants Of Non-Performing Loans In Nigeria,"Accounting & Taxation, The Institute for Business and Finance Research, 6(2), 21-28, Retrieved from http://www.theibfr2.com/

Allen, L. & Saunders, A. (2002). A Survey of Cyclical Effects in Credit Risk Measurement Models. SSRN Electronic Journal. doi:10.2139/ssrn.315561.

Alves, I. (2004). Corporate fragilitys sectoral dynamics and determinants: evidence from expected default measures, mimeo, European Central Bank.

Assouan, S. (2012). Stress testing a retail loan portfolio: an error correction model approach. The Journal of Risk Model Validation, 6(2), 3-25. doi:10.21314/JRMV.2012.082.

Badar.M. & Javid.A. (2013). Impact of macroeconomic forces on nonperforming loans: An empirical study of commercial banks in Pakistan. WSEAS Transactions on Business and Economics, 10(1), 40-48.

Beck, Roland & Jakubik, Petr & Piloiu, Anamaria. (2015). Key Determinants of Non-performing Loans: New Evidence from a Global Sample. Open Economies Review, doi: 26. 10.1007/s11079-015-9358-8.

Boss, M. (2002). A macroeconomic credit risk model for stress testing the Austrian credit portfolio. Financial Stability Report. 4. 64-82.

Castro, V. (2012). Macroeconomic Determinants of the Credit Risk in the Banking System: The Case of the GIPSI. Economic Modelling. 31. 672–683. dio: 10.1016/j.econmod.2013.01.027.

Cihak, M. (2007). Introduction to Applied Stress Testing. IMF Working Papers, 07, 1-74. doi: 10.5089/9781451866230.001.

Dash. M. & Kabra. G.(2010). The Determinants of Non-Performing Assets in Indian Commercial Bank: An Econometric Study. Middle Eastern Finance and Economics. 7. 94-106.

Davis, E & Karim, D. (2008). Comparing early warning systems for banking crises. Journal of Financial Stability. doi: 4. 89-120. 10.1016/j.jfs.2007.12.004.

Dovi, S.A., Mireille, B., Jardet, C., Kendaoui, L. & Moquet, J. (2009). Macro Stress Testing with a Macroeconomic Credit Risk Model: Application to the French Manufacturing Sector. Banque de France Working Paper, 238. doi:10.2139/ssrn.1666737.

Eichengreen, B. & Rose,A. (1998), Staying Afloat When the Wind Shifts: External Factors and Emerging-Market Banking Crises. NBER Working Paper, 6370, DOI : 10.3386/w6370.

Ekanayake, N & Azeez, A. (2015). Determinants of Non-Performing Loans in Licensed Commercial Banks: Evidence from Sri Lanka. Asian Economic and Financial Review. 5. 868-882. doi: 10.18488/journal.aefr/2015.5.6/102.6.868.882.

Espinoza. R & Prasad. A. (2010). Nonperforming Loans in the GCC Banking System and their Macroeconomic Effects. IMF Working paper,10/224. doi:10.5089/9781455208890.001.

Festic, M., Kavkler, A. & Repina, S. (2011). The macroeconomic sources of systemic risk in the banking sectors of five new EU member states. Journal of Banking and Finance. 35, 310-322. doi: 10.1016/j.jbankfin.2010.08.007.

Figlewski,S., Frydman,H., & Liang,W.(2012). Modeling the effect of macroeconomic factors on corporate default and credit rating transitions.

International Review of Economics & Finance, 21(1), 87-105. doi: 21.10.2139/ssrn.934438.

Foglia, A.2009. Stress Testing Credit Risk: A Survey of Authorities' Approaches. International Journal of Central Banking, 5(3), 9-45. doi: 10.2139/ssrn.1396243 .

Hippolyte. L.F.(2005). Nonperforming loans in Sub-Saharan Africa: causal analysis and macroeconomic implications. World Bank Policy Research Working Paper ,3769.. Retrieved from https://ssrn.com/abstract=849405.

Jiménez, G. & Saurina, J. (2006). Credit Cycles, Credit Risk, and Prudential Regulation. International Journal of Central Banking. Retrieved from https://www.ijcb.org/journal/ijcb06q2a3.htm.

Kattai, R. (2010). Credit risk model for the Estonian banking sector. Bank of Estonia Working Papers, wp2010-01, Retrieved from https://www.eestipank.ee/.

Kearns, A. (2004). Loan Losses and the Macroeconomy: A Framework for Stress Testing Credit Institutions' Financial Well¬ Being, Financial Stability Report, Retrieved from https://www.researchgate.net/

Khemraj, T. & Pasha, S.(2016). Determinants of Nonperforming Loans in Guyana. doi: 10.1057/978-1-137-52246-7_9.

Klomp, J. (2010). Causes of banking crises revisited. North American Journal of Economics and Finance, 21(1), 72-87, doi: 10.1016/j.najef.2009.11.005.

Kucukkocaoglu, G. & Altintas, M. (2016). Using non-performing loan ratios as default rates in the estimation of credit losses and macroeconomic credit risk stress testing: A case from Turkey, Risk governance & control. financial markets & institutions, 6(1), 52-63. doi:10.22495/rgcv6i1art6.

Kucukozmen, C. & Yuksel.A. (2006). A macroeconometric model for stress testing credit portfolio. 13th Annual Conference of the Multinational Finance Society, June 2006. Retrieved from http://www.coskunkucukozmen.com/

Kumarasinghe, P. J. (2017). Determinants of Non Performing Loans: Evidence from Sri Lanka. International Journal of Management Excellence. 9(2), 1113 – 1121. Retrieved from https://www.researchgate.net/

Llewellyn, D. (2002). An Analysis of the Causes of Recent Banking Crises. European Journal of Finance, 8(2), 152-175. doi: 10.1080/13518470110071182.

Lobna, A. & Ouertani, N. & Sonia, Z. G. (2014). Macroeconomic and Bank-specific Determinants of Household's Non-performing Loans in Tunisia: A Dynamic Panel Data. Procedia Economics and Finance. 13. 58–68. doi :10.1016/S2212-5671(14)00430-4.

Louzis, D. P., Vouldis, A. T. & Metaxas, V. L. (2010). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios, Journal of Banking & Finance. Elsevier,36(4), 1012-1027. doi: 10.1016/j.jbankfin.2011.10.012.

Messai, A.S.& Jouini,F. (2013). Micro and Macro Determinants of Non-performing Loan. International Journal of Economics and Financial Issues, 3(4), 852-860. Retrieved from http://www.econjournals.com/

Mohammadrez.A. & Muhammad.J. (2013). Non-Performing Loans Sensitivity to Macro Variables: Panel Evidence from Malaysian Commercial Banks. American Journal of Economics, 3(5C), 16-21 doi: 10.5923/c.economics.201301.04.

Ngerebo, T. (2012). The impact of foreign exchange fluctuation on the intermediation of banks in Nigeria . African journal of business management, 6. doi: 3872. 10.5897/AJBM09.113.

Oanh. Vu & H. Vu, Yen & T. T. Nguyen, Trang & Bui Trung, Hau. (2018). A Framework for Macro Stress-Testing the Credit Risk of Commercial Banks: The Case of Vietnam. Asian Social Science, 14. 1. doi:10.5539/ass.v14n2p1.

Otani, A., Shiratsuka, S., Tsurui, R., Yamada,T.(2009). Macro Stress Testing on the Loan Portfolio of Japanese Banks. Bank of Japan Working Paper Series, 9(E-1). doi:RePEc:boj:bojwps:09-e-1.

Ouhibi.S & Amami.S. (2015). Determinants of Non-performing loans in the southern Mediterranean countries. International Journal of Accounting & Economics Studies, 3 (1), 50-53.

Pesaran, H., schuermann, T., Treutler, B. & Weiner, S. (2003). Macroeconomic Dynamics and Credit Risk: A Global Perspective. Journal of Money, Credit and Banking. Retrieved from http://citeseerx.ist.psu.edu/

Rinaldi, L. & Sanchis, A. (2006). Household debt sustainability: what explains household non-performing loans? An empirical analysis, Working Paper Series 570, European Central Bank. doi: RePEc:ecb:ecbwps:2006570.

Salas, J.V. & Saurina,S. J. (2002). Credit Risk in Two Institutional Regimes: Spanish Commercial and Savings Banks. Journal of Financial Services Research, 22(3), Retrieved from SSRN: https://ssrn.com/.

Sommar, A & Hovick, S. (2008). Macroeconomic Impact on Expected Default Frequency Riksbank Research Paper Series, 51, doi.org/10.2139/ssrn.1088626, Retrieved from http://citeseerx.ist.psu.edu/

Sorge, M.& Virolainen, K. (2006). A comparative analysis of macro stress-testing methodologies with application to Finland. Journal of Financial Stability. 2. 113-151. doi:10.1016/j.jfs.2005.07.002.

Thiagarajan,S., Ayyappan.S. & Ramachnadran.A. (2011). Credit Risk Determinants of Public and Private Sector Banks in India. European Journal of Economics, Finance and Administrative Sciences. 34 (2011), 147-154, Retrieved from http://www.eurojournals.com.

Tian.R. & Yang.J. (2011). Macro Stress Testing on Credit Risk of Commercial Banks in China Based on Vector Autoregression Models. doi:10.2139/ssrn.1909327.

Vazquez, F., Tabak, B. M. & Souto, M. (2012). A macro stress test model of credit risk for the Brazilian banking sector. Journal of Financial Stability, Elsevier, 8(2), 69-83.doi : 10.1016/j.jfs.2011.05.002.

Virolainen, K. (2004). Macro Stress Testing with a Macroeconomic Credit Risk Model for Finland. Bank of Finland Discussion Paper. 18/2004. doi.org/10.2139/ssrn.622682.

Vogiazas, S. D. and Nikolaidu, E. (2011) "Investigating the Determinants of Nonperforming Loans in the Romanian Banking System: An Empirical Study with Reference to the Greek Crisis", Hindawi Publishing Corporation Economics Research International, Article ID 214689.13, doi:101155/2011/214689

Wong, J., Choi, K & Fong,T. (2008). A Framework for Stress Testing Banks' Credit Risk. The Journal of Risk Model Validation, 2(1), 3-23, Retrieved from https://ssrn.com/abstract=1327561.

Wulandari, Y., Musdholifah, & Suhal, K. (2017). The impact of macroeconomic and internal factors on banking distress. International Journal of Economics and Financial Issues, 2017, 7(3), 429-436, Retrieved from http://www.econjournals.com/.

Yurdakul, F. (2013). Macroeconomic Modeling of Credit Risk for Banks. Procedia-Social and Behavioral Sciences, 109(2014), 784-793. doi: org/10.1016/j.sbspro.2013.12.544.

Appendix A: ADF Test results of model variables

Null Hypothesis: D(NPL) has a unit root
Exogenous: Constant
Lag Length: 8 (Automatic based on SIC, MAXLAG=9)

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			**-4.0778**	**0.0038**
Test critical values:	**1% level**		**-3.67932**	
	5% level		**-2.96777**	
	10% level		**-2.62299**	
*MacKinnon (1996) one-sided p-values.				

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NPL,2)
Method: Least Squares
Date: 04/20/19 Time: 16:07
Sample (adjusted): 2011Q3 2018Q3
Included observations: 29 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(NPL(-1))	**-1.19648**	**0.293412**	**-4.0778**	**0.0006**
D(NPL(-1),2)	**0.708903**	**0.262556**	**2.700012**	**0.0142**
D(NPL(-2),2)	**0.697196**	**0.262265**	**2.658363**	**0.0155**
D(NPL(-3),2)	**0.18802**	**0.220465**	**0.852836**	**0.4044**
D(NPL(-4),2)	**0.782262**	**0.203852**	**3.837405**	**0.0011**
D(NPL(-5),2)	**0.629604**	**0.250801**	**2.510376**	**0.0213**
D(NPL(-6),2)	**0.297998**	**0.188222**	**1.583225**	**0.1299**
D(NPL(-7),2)	**0.47487**	**0.182241**	**2.605725**	**0.0174**
D(NPL(-8),2)	**0.573038**	**0.169152**	**3.387698**	**0.0031**
C	**0.026315**	**0.015084**	**1.744601**	**0.0972**

R-squared	0.822912		
Adjusted R-squared	0.739029	Mean dependent var	-0.00731
S.E. of regression	0.063057	S.D. dependent var	0.123435
Sum squared resid	0.075548	Akaike info criterion	-2.42275
Log likelihood	45.12986	Schwarz criterion	-1.95127
F-statistic	9.810166	Hannan-Quinn criter.	-2.27509
Prob(F-statistic)	0.000019	Durbin-Watson stat	1.927443

Null Hypothesis: D(GDP) has a unit root Exogenous: Constant Lag Length: 0 (Automatic based on SIC, MAXLAG=9)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			**-7.50379**	**0.0000**
Test critical values:	**1% level**		**-3.62102**	
	5% level		**-2.94343**	
	10% level		**-2.61026**	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation Dependent Variable: D(GDP,2) Method: Least Squares Date: 04/20/19 Time: 16:03 Sample (adjusted): 2009Q3 2018Q3 Included observations: 37 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(GDP(-1))	**-1.23322**	**0.164347**	**-7.50379**	**0**
C	**0.050987**	**0.207456**	**0.245772**	**0.8073**
R-squared	0.616677			
Adjusted R-squared	0.605725	Mean dependent var		-0.02473
S.E. of regression	1.260412	S.D. dependent var		2.007303
Sum squared resid	55.60234	Akaike info criterion		3.353293
Log likelihood	-60.0359	Schwarz criterion		3.440369
F-statistic	56.30687	Hannan-Quinn criter.		3.383991
Prob(F-statistic)	0	Durbin-Watson stat		1.893891

Null Hypothesis: D(UNEMP) has a unit root Exogenous: Constant Lag Length: 1 (Automatic based on SIC, MAXLAG=9)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			**-5.85399**	**0.0000**
Test critical values:	**1% level**		**-3.62678**	
	5% level		**-2.94584**	
	10% level		**-2.61153**	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation Dependent Variable: D(UNEMP,2) Method: Least Squares Date: 04/21/19 Time: 05:51 Sample (adjusted): 2009Q4 2018Q3 Included observations: 36 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(UNEMP(-1))	**-1.60198**	**0.273656**	**-5.85399**	**0.0000**
D(UNEMP(-1),2)	**0.218543**	**0.163849**	**1.333803**	**0.1914**
C	**-0.07311**	**0.059126**	**-1.23655**	**0.225**
R-squared0.665252 Adjusted R-squared0.644964 S.E. of regression0.349531 Sum squared resid4.03167 Log likelihood-11.6737 F-statistic32.79078 Prob(F-statistic)0		Mean dependent var-0.00556 S.D. dependent var0.58661 Akaike info criterion0.815206 Schwarz criterion0.947165 Hannan-Quinn criter0.861263 Durbin-Watson stat1.993669		

Null Hypothesis: D(EXRT) has a unit root Exogenous: Constant Lag Length: 0 (Automatic based on SIC, MAXLAG=9)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			**-6.30481**	**0.0000**
Test critical values:	**1% level**		**-3.62102**	
	5% level		**-2.94343**	
	10% level		**-2.61026**	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation Dependent Variable: D(EXRT,2) Method: Least Squares Date: 04/20/19 Time: 15:59 Sample (adjusted): 2009Q3 2018Q3 Included observations: 37 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(EXRT(-1))	**-1.02717**	**0.162918**	**-6.30481**	**0.0000**
C	**0.202144**	**0.41122**	**0.491572**	**0.6261**

R-squared	0.531777		
Adjusted R-squared	0.518399	Mean dependent var	0.172162
S.E. of regression	2.501189	S.D. dependent var	3.604149
Sum squared resid	218.9581	Akaike info criterion	4.723948
Log likelihood	-85.393	Schwarz criterion	4.811024
F-statistic	39.75066	Hannan-Quinn criter.	4.754646
Prob(F-statistic)	0	Durbin-Watson stat	1.998079

Appendix B: Vector Error Correction Model Estimates

Sample (adjusted): 2009Q4 2018Q3				
Included observations: 36 after adjustments				
Standard errors in ( ) & t-statistics in [ ]				
Cointegrating Eq:	CointEq1	CointEq2	CointEq3	
NPLR(-1)	1	0	0	
UNEMP(-1)	0	1	0	
EXRT(-1)	0	0	1	
GDP(-1)	-0.41561	0.083739	2.332697	
	-0.14998	-0.04977	-0.48483	
	[-2.77118]	[1.68239]	[4.81138]	
C	-2.04686	-4.98301	-116.672	
Error Correction:	D(NPLR)	D(UNEMP)	D(EXRT)	D(GDP)
CointEq1	-0.48705	0.279112	0.997902	0.454733
	-0.15592	-0.11164	-1.08954	-0.3953
	[-3.12376]	[2.50008]	[0.91589]	[1.15035]
CointEq2	0.825965	-1.25189	-3.41946	-0.16084
	-0.49707	-0.35591	-3.4735	-1.26022
	[1.66166]	[-3.51738]	[-0.98444]	[-0.12762]
CointEq3	-0.08011	0.010862	-0.1557	-0.11554
	-0.02335	-0.01672	-0.16315	-0.05919
	[-3.43143]	[0.64973]	[-0.95432]	[-1.95201]
D(NPLR(-1))	0.426972	-0.10066	-2.62836	-0.03535
	-0.18326	-0.13122	-1.28059	-0.46461
	[2.32990]	[-0.76715]	[-2.05246]	[-0.07607]
D(NPLR(-2))	0.416866	-0.09875	-0.444	0.093568
	-0.1905	-0.1364	-1.33122	-0.48298
	[2.18824]	[-0.72393]	[-0.33353]	[0.19373]
D(UNEMP(-1))	-0.72366	0.062886	2.445436	-0.24138
	-0.3903	-0.27947	-2.72741	-0.98953
	[-1.85408]	[0.22502]	[0.89661]	[-0.24393]
D(UNEMP(-2))	-0.53095	-0.05858	0.930031	0.451542
	-0.25304	-0.18118	-1.7682	-0.64152
	[-2.09830]	[-0.32333]	[0.52598]	[0.70386]
D(EXRT(-1))	0.080261	0.019434	0.047816	0.113733
	-0.03558	-0.02547	-0.24861	-0.0902
	[2.25597]	[0.76288]	[0.19233]	[1.26092]
D(EXRT(-2))	0.063829	s0.044486	0.219463	0.204809
	-0.03145	-0.02252	-0.21974	-0.07972
	[2.02982]	[1.97574]	[0.99874]	[2.56897]

D(GDP(-1))	-0.03011	0.088827	0.532533	-0.34877
	-0.0859	-0.0615	-0.60024	-0.21777
	[-0.35050]	[1.44425]	[0.88720]	[-1.60154]
D(GDP(-2))	0.008618	0.01715	0.314183	-0.19518
	-0.068	-0.04869	-0.4752	-0.17241
	[0.12673]	[0.35222]	[0.66116]	[-1.13206]
C	-0.08282	-0.08251	-0.13844	-0.0116
	-0.06791	-0.04862	-0.47453	-0.17216
	[-1.21965]	[-1.69696]	[-0.29174]	[-0.06737]
R-squared	0.672651	0.636154	0.258755	0.595966
Adj. R-squared	0.554419	0.469391	-0.08098	0.410783
Sum sq. resids	2.726451	1.70462	162.3566	21.37123
S.E. equation	0.360321	0.266507	2.600934	0.943646
F-statistic	3.08227	3.814718	0.761634	3.218262
Log likelihood	-4.63246	3.82139	-78.1948	-41.6953
Akaike AIC	1.090692	0.454367	5.01082	2.98307
Schwarz SC	1.750492	0.982207	5.53866	3.51091
Mean dependent	-0.14444	-0.05	0.21	-0.03659
S.D. dependent	0.48782	0.365865	2.501613	1.229339
Determinant resid covariance (dof adj.)		0.049433		
Determinant resid covariance		0.009765		
Log likelihood		-121.005		
Akaike information criterion		10.05585		
Schwarz criterion		12.69505		