DEBT CRISES, CREDIT CYCLES AND ECONOMIC GROWTH IN INDONESIA

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Abstract

The aim of this thesis is threefold: to develop economic models to predict external debt crises using penalized regression approach and Artificial Neural Network (ANN), investigate the optimal level of local government debt, and study the characteristics and determinants of the credit cycle in Indonesia. In the first study, Firth’s penalized logistic regression is adopted to investigate Indonesia’s external debt crisis. The results show that GDP growth and public debt to GDP ratio are among the most significant indicators for the prediction of a debt crisis. The probability of a debt crisis increases by 63 percent as GDP growth falls by 1 percent, while an increase in the public debt-to-GDP ratio of 1 percent will increase the probability of a debt crisis by around 80 percent. Further to this, event study analysis is utilized in the analysis to examine the behavior of macroeconomic indicators during the times of external debt crisis. The results suggest that short-term debt, debt service, debt maturity and central government debt increase significantly during times of crises as compared to their values during the normal times.

In the second study, the ANN model is developed for predicting Indonesia’s external debt crisis. The findings suggest that exchange rate, foreign reserves, and exports are the major determinants for predicting external debt crisis. The performance of the ANN model in correctly predicting in-sample and out-of-sample external debt crises is also compared. The ANN in-sample performance provides relatively superior results, as the model can classify correctly 89.12 percent of the crises. However, the performance of the out-of-sample prediction is not as good as the in-sample prediction. It is argued that the ANN model tends to over-fit the data for the in-sample prediction, while it cannot fit the out-of-sample very well. The ANN model can be used to identify past crisis episodes with a higher degree of accuracy, but predicting crises outside of the estimation sample presents a greater challenge due to the uncertainty that may be present in the estimation.

In the third study, characteristics of credit cycles, cycle co-movements among credit variables and determinants of the credit boom in Indonesia are investigated. The findings suggest that Indonesia experienced more episodes of credit booms than credit busts. When credit booms take place, they persist for longer, and are followed by the credit busts which are short-lived and deeper. The results demonstrate a significant and positive relationship between credit growth and new credit approval ratio to the occurrence of the credit booms. A rapid credit growth and higher ratio of new credit approval contribute not only to the
increased possibility of the credit booms, but also to a higher magnitude of the credit boom. The results also find that a lower policy rate increased the possibility of the credit booms. For the magnitude of the credit booms, an increase in residential house price index and GDP growth increase the magnitude of the credit booms, while a rise in inflation decreases the magnitude of the credit booms.

In the fourth study, the relationship between local government debt and regional growth in Indonesia is examined using an augmented growth model. The negative coefficient of the quadratic form of local debt-to-GDP suggests a concave or inverted U-shaped relationship between local government debt and regional growth. The results confirm the theoretical assumption that at low debt levels the impact on growth is positive, but beyond the debt threshold, an adverse effect on regional growth prevails. There is also no evidence that a reverse causal effect exists between local debt and regional growth in Indonesia.
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List of Abbreviations

AFC  Asian Financial Crisis
ANN  Artificial Neural Network
BP   Back-Propagation
CCB  Cyclical Capital Buffer
CPI  Consumer Price Index
DSR  Debt Service Ratio
EWS  Early Warning System
FE   Fixed Effect
FTV  Financing-to-Value
GFC  Global Financial Crisis
GMM  Generalized Method of Moments
GRP  Gross Regional Product
HDI  Human Development Index
HP   Hodrick-Prescott
IMF  International Monetary Fund
IUIDP Integrated Urban Infrastructure Development Programs
KMO  Kaiser-Meyer-Olkin
LTV  Loan-to-Value
NIM  Net Interest Margin
NPL  Non-Performing Loan
OLS  Ordinary Least Square
PCA  Principal Component Analysis
POPG Population Growth
PPP  Public Private Partnership
RDA  Regional Development Account
RE   Random Effect
S&P  Standard & Poor
SLA  Subsidiary Loan Agreement
SME  Small Medium Enterprises
SOE  State Owned Enterprises
TME  Total Misspecification Error
UWA  University of Western Australia
VGF  Viability Gap Funding
YOY  Year-on-year
Chapter 1  INTRODUCTION

1.1 Background

Many developed and emerging economies have experienced multiple external debt crises in recent years due to the effects of poor sovereign debt control and planning. Indonesia is no exception. No countries are immune to external debt crises, and this is particularly true once an economy has achieved some degree of capital account liberalization and financial deregulation. Such a position is unsustainable especially for countries that have no prudent monetary or robust macro-prudential policies in place. In the instance of an excessive external debt level, accrued from a country’s policy failures in controlling external debt, there are many examples of countries that have suffered from resulting external debt crises.

Some developing countries are being driven into external debt turmoil as a result of unmanageable and ballooning external debt levels. Indonesia falls among the group of countries that has used external debt as a source of funding to cover a budget deficit. Even though Indonesia has set a maximum budget deficit limit of three percent of GDP\(^2\); it remains unclear what the exact consequences are for the government when this cap is breached. For example, budget deficit in 2006 almost reached the legally allowed limit due to massive revenue shortfalls and an unprecedented increase in government expenditures, but there is no legal action taken. The problem is even further exacerbated when the domestic debts are used to finance budget deficit. Proceeding along this path and incurring both large external and

\(^2\) This policy was adopted in 2003 after Indonesia experienced the devastating effects of the Asian Financial Crisis in the late 1990s, and these traumatic experiences made the government decide to prioritize prudent fiscal policies.
internal debts can create a situation called as debt spiral, where a country experiences ever-increasing unsustainable high levels of debt. This can lead to a debt crisis.

The external debt crisis in Indonesia can be traced back to the Asian Financial Crisis (AFC) in 1998/1999. Indonesia borrowed heavily from international markets due to low global interest rates. As a result, there is a growing level of external debt prior to the AFC. Additionally, Indonesia has an over-reliance on short-term external debt financing, and at that time they are accounted for 85 percent of Indonesia's total external debts. Indonesia is one of the countries that is most severely affected by the AFC, as its GDP dropped more than 13 percent and its currency lost over 80 percent of its value against the US dollar. The significant devaluation of the Rupiah resulted in many Indonesian financial institutions defaulting on their external debts. There are also sudden large capital flow reversal, increases in unemployment and declines in asset prices during the external debt crisis. The impact of this crisis is a sharp increase in external debt service obligations, and the debt-to-GDP ratio increased to an unsustainably high level of 146 percent.

The costs associated with an external debt crisis are enormous. Furceri and Zdzienicka (2012) argue that external debt crises have detrimental impacts on the economy both in the short-term and the long-term. Based on studies of an unbalanced panel of 154 countries from 1970 to 2008, they suggest that in the short-term, debt crises negatively affect output growth, with the magnitude of the effect around eight percentage points. In the medium-term, their analyses also confirm the negative effect of debt crises on output growth, as it can reduce the level of output even further by about 10 percent. The external debt crisis also poses other risks such as the loss of investor confidence, which can lead to a significant increase in interest rate and the cost of funds for future borrowing.

There is a close relationship between the credit cycle and government debt. Indonesia has enjoyed high level of credit growth in recent years, as the Financial Services Authority
(OJK) reports that average annual credit growth in Indonesia is about 16.3 percent between 2002 and 2016. Indonesia’s rapid credit expansion in recent years can be attributed to a stable macroeconomic environment, robust economic growth and availability of new lending instruments (IMF, 2016). The country is also still in its developmental phase, and as such, credit tends to grow at a faster pace than output. A situation like this is not only observed in Indonesia, but also in some developed countries which may experience faster growth in credit than output due to financial liberalization (Aikman et al., 2015). As Indonesia’s development goals involve more pronounced economic growth, strong credit growth thus ensues (Elekdag and Wu, 2011). Whilst rapid credit growth can be associated with excessive credit expansions, at the end of the credit boom, this growth will eventually be followed by credit contractions.

There exist relatively few studies analyzing the impact of local debt on economic growth, which include Indonesian data. One possible explanation is that there is limited data available to facilitate comprehensive study on how regional debts affect regional growth (Wu, 2014). Many studies examine the relationship between economic growth at the country level but fall short of completing an investigation of the effects at the regional level. With the occurrence of the major crisis during the AFC and GFC, the focus of many studies shifted towards country level analysis, instead of regional level (Georgiev, 2012). For Indonesia, Petersen and Tirtosuharto (2012) also argue that local government debts are too insignificant to warrant further investigation, as the local debt as a percentage of GDP is less than one percent.

Motivated by the complex issues associated with Indonesia’s external debt crisis, local government debt and credit cycle, it is imperative to study these problems in order to provide future potential solutions to mitigate the adverse impacts of these crises. This study aims to develop economic models for predicting external debt crises, investigate the optimal
level of local government debts and examine the characteristics and determinants of the credit cycles in Indonesia.

1.2 Research Objectives and Contributions

The first study identifies the macroeconomic and debt characteristics associated with times of external debt crisis in Indonesia. This study adopts a penalized logistic regression as opposed to a standard logistic regression. When the standard logistic regression is applied, the findings suggest that a separation problem occurs, where one or more predictors perfectly predict the incidence of the external debt crisis. This study uses a penalized logistic regression approach, as it solves the separation problem resulting from the standard logistic regression by reducing biased estimation parameters.

The second study uses an Artificial Neural Network (ANN) approach for predicting external debt crises in Indonesia. There are relatively few papers in the existing literature focusing on Indonesia’s early warning system (EWS) for external debt crisis prediction. Thus far, there are no previous studies investigating the use of EWS to predict external debt crises in Indonesia. This study exploits the ANN model, as it has the advantage of being able to detect complex non-linear relationships between the predictor and dependent variables implicitly. This study also attempts to improve the predictive power of the ANN model for the prediction of Indonesia’s external debt crises.

The third study, focusing on credit cycles, presents some empirical evidence on the characteristics of the credit cycles in Indonesia, including credit booms and busts. Cycle co-movements among credit variables and determinants of credit booms are also investigated. This study offers policy suggestions that may be useful in order to mitigate the adverse impacts of the credit crisis in Indonesia.
The fourth study aims to extend the work of Wu (2014) by presenting an empirical analysis of the relationship between local debt and regional growth in Indonesia. The significance of the study lies primarily in its important contribution to determining the optimal point of the local debt level, which local governments can adopt to achieve higher regional growth.

1.3 Thesis Structure

The next chapter (Chapter 2) first examines the definition of external debt crisis prediction. This section explores various definitions of an external debt crisis, for instance, a sovereign default, which can be defined as large arrears of debt, or distressed events, when a country has difficulty in servicing a debt obligation, alongside some other definitions of a debt crisis (Ciarlone and Trebeschi, 2005). Various definitions of the debt crisis are advanced, which provide a basis for determining the episodes of external debt crises in Indonesia. This chapter also provides a conceptual and analytical framework using a penalized logistic regression approach, as well as demonstrating how this model can be used to predict Indonesia’s external debt crisis. In this study, this approach has been effective in addressing a separation problem, where one or more predictors can predict perfectly the occurrence of the external debt crisis, which is typical in the small data set environment. Furthermore, event study analysis is used to observe the behavior of macroeconomic indicators during the times of external debt crisis.

Chapter 3 develops the ANN model for predicting external debt crises in Indonesia. As a tool for forecasting and classifying, the ANN model has been instrumental and widely used for prediction in many fields, including economics and finance. Due to its superiority and the robustness of the results, this study adopts the ANN with a back-propagation (BP)
algorithm in order to assess and predict the external debt crisis in Indonesia. This study compares the performance of the ANN model in correctly predicting in-sample and out-of-sample external debt crises. There are five indicators used in the study, including foreign reserve export, import, exchange rate and foreign debt repayment. Later in the study, indicators with the high predictive power in explaining external debt crises in Indonesia are also investigated.

Chapter 4 presents some empirical evidence on the characteristics of credit cycles in Indonesia, including the episodes of credit booms and busts. Moreover, this section examines specific characteristics of credit sub-components including working capital, investment and consumption credit. Cycle co-movements among credit variables and determinants of credit booms in the country are also investigated in detail.

Chapter 5 focuses on the relationship between local government debt and regional economic growth in Indonesia. This study uses an augmented growth model to examine the relationship between local debt and regional growth in Indonesia. Several indicators including Gross Regional Product (GRP)-per-capita, local government debt, population growth, Human Development Index (HDI), investment-to-GRP, fiscal capacity ratio and Consumer Price Index (CPI) are used to examine those relationships. Furthermore, the chapter touches on various economic theories, including the debt Laffer curve that has been advanced to explain the relationship between local debt and regional growth. The endogeneity problems of the possible causal relationship between regional GDP and local debt are also addressed in this section.

Finally, Chapter 6 summarizes main findings. This chapter highlights some policy suggestions and possible future directions for research that will enable improvement and extension of the current research.
2.1 Introduction

Despite the existence of a wealth of literature on the use of EWS for predicting financial crises, the determinants of a debt crisis for a country are yet to be understood. This paper identifies macroeconomic and debt indicator characteristics during times of crisis and applies a penalized logistic regression for debt crises prediction in order to reduce biased estimation parameters in the standard logistic regression.

Previous studies, using data from both developed and developing economies, have examined the usefulness of macroeconomic and debt indicators for predicting an external debt crisis. However, this is the first study to extend the analysis using a penalized regression model to estimate the likelihood of a debt crisis in Indonesia. The main reason for using a penalized logistic regression model, rather than the standard logistic regression model, is to overcome a separation problem that may occur in small data set environments where one or more variables perfectly predict the occurrence of the external debt crises. Using standard logistic regression, the results show that the separation problem exists when the public debt-to-GDP ratio perfectly predicts external debt crisis. The penalized regression model addresses this problem.

The chapter proceeds as follows. Section 2.2 presents a review of the literature, including definitions of debt crises and previous studies in debt crises prediction. The
penalized regression model is presented in Section 2.3. Section 2.4 describes the data. Section 2.5 discusses empirical results, and Section 2.6 presents the conclusions.

2.2 Review of Literature

The purpose of this section is to review the existing literature and discuss the concept development of EWS for debt crises. This section provides a useful foundation for determining the major factors in the choice of econometric model for the analysis of debt crises. There are no single definitions of external debt crises. For example, Pescatori and Sy (2007) classify external debt crises as sovereign defaults indicated by large debt arrears, large IMF loans, or distress events.

2.2.1 Debt Crises as Sovereign Defaults

Rating agencies mainly focus on default events and use credit rating scores as a proxy for the probability of default. Moody’s (2003) defines a sovereign default as occurring when there is either (i) a missed or delayed disbursement of interest and/or principal, or (ii) when the there is a distressed exchange occurring, whereby the issuers offer bondholders a new security or package of securities with a diminished financial obligation (such as new debt instruments with a lower coupon or par value).

Standard & Poor’s (S&P) defines debt default as the failure of an obligor to meet the principal or interest payment on the due date or within the specified grace period contained in the original terms of the debt issue (Chambers and Alexeeva, 2003). With regards to local
and foreign currency bonds, notes and bills, debtors are considered to have defaulted when
either the scheduled debt service is not paid on the due date or when the exchange offer of
new debt contains less favourable terms than the original issue. For central bank currency,
default occurs when notes are converted into a new currency of less-than-equivalent face
value. For bank loans, default occurs when the scheduled debt service is not paid on the due
date or when there is a negotiation of the loan principal and interest on less favourable terms
than the original loan.

Reinhart et al. (2003) consider debt crises derived from the S&P definition and goes
on to discover that 36 out of 53 debt crises in emerging countries occurred between the period
1970 and 2000. According to Calomiris and Beim (2000), a country is officially in debt
default if all or part of the interest and/or principal payments are significantly reduced or
rescheduled.

2.2.2 Debt Crises as Large Arrears

Detragiache and Spilimbergo (2001) consider a country to be in a debt crisis if it has arrears
to commercial creditors exceeding more than 5 percent of total arrears for principal and/or
interest payments. They also define a debt crisis as having occurred when a country
reschedules or restructures their debt agreements with commercial creditors.

Peter (2002) defines debt default by considering changes in the level of debt arrears
and the amount rescheduled. A country is considered to default when either there is an
increase in the total stock of long-term debt arrears (both principal and interest) to creditors
of more than 2 percent of the total external debt, or when the total amount of long-term debt
rescheduled in any given year exceeds 2.5 percent of the total external debt.
De Paoli et al. (2006) define a debt crisis as occurring when a country has large debt arrears (on principal or interest payments), or if a country arranges a rescheduling agreement with its foreign private creditors. They also define the country as being in default when the level of arrears on principal and interest exceeds 15 or 5 percent, respectively.

2.2.3 Debt Crises as Large IMF Loans

Manasse et al. (2003) define a country to be in a debt crisis when it is classified as being in default by S&P, or if it receives a large, non-concessional IMF loan, that is, in excess of 100 percent of the quota. S&P rates sovereign issuers as being in default if a government fails to meet principal or interest payments on external obligations on the given due date, including exchange offers, debt-equity swaps, and buy-backs for cash.

2.2.4 Debt Crises as Distress Events

Sy (2004) defines debt crises as situations of sovereign distress when the average spread on liquid sovereign bonds is above 1000 basis points of US Treasury Securities. The choice of using the 1000 bps gap above the US Treasury as a threshold is considered to represent a psychological barrier by market participants.
2.2.5 Other Definitions of Debt Crises

Kraay and Nehru (2006) define debt crises as occurring when countries not only have substantial arrears on their external debts but when they also resort to debt relief from the Paris Club of creditors or request non-concessional balance of payment support from the International Monetary Fund (IMF).

Cohen and Valadier (2010) go on to modify this definition of debt distress proposed by Kraay and Nehru (2006). They propose that a country experiences a debt crisis when total arrears of principal and/or interest on long-term debt to all creditors exceeds 5 percent of the total debt outstanding, or a country receives debt relief from the Paris Club or receives significant balance of payment support from the IMF (in the form of stand-by arrangement or extended fund facilities).

Ucal and Oksay (2011) define a debt crisis as occurring when a country is unable to repay its overseas debts to non-resident lenders. A solvency ratio indicator of external debt - the current account plus capital account over the principal and interest payment - is used in their EWS as a proxy for an economy’s ability to repay its overseas debts to non-resident lenders.

As noted in the introduction, an external debt crisis is defined when either there are large arrears on external obligations of more than 5 percent of total debt stocks (Detragiache and Spilimbergo, 2001; Kraay and Nehru, 2006; Ciarlone and Trebeschi, 2005; De Paoli et al., 2006; Cohen and Valadier, 2010) or there are rescheduling or restructuring agreements leading to less favourable terms to lenders than in the original arrangement (Chambers and Alexeeva, 2003; Ciarlone and Trebeschi, 2005; Rogoff and Reinhart, 2010).
2.2.6 **Previous Studies**

There is a large body of literature considering EWS methods for predicting debt crises, including the logistic regression model (Manasse et al., 2003; Ciarlone and Trebeschi, 2005; Fuertes and Kalotychou, 2007), binary recursive trees (Manasse et al., 2003; Roubini and Manasse, 2005), and recently, methods of Artificial Neural Network (Fioramanti, 2008).

Each EWS method has its advantages and disadvantages. The main advantage of the logistic model is that it enables measurement of the effect of each explanatory variable on the probability of crisis. It is also most suited to predict a binary outcome from a vector of explanatory variables. The logistic regression model is a parametric method, as it generates confidence intervals for the coefficient values. However, the logistic regression model has several disadvantages. Unlike linear regression, the logistic regression can only be used to predict discrete functions, and the dependent variable of the logistic regression is restricted to the discrete number set. Logistic regression also relies heavily on large samples, while small sample sizes can lead to inaccurate estimates of parameters.

The binary recursive tree exhibits a number of distinctive features. This method is non-parametric and robust to the presence of outliers among the independent variables (Manasse et al., 2003). The binary tree searches for patterns and relationships in the data and is particularly appropriate for uncovering hidden, non-linear structures and interactions in complex data sets. Missing values for predictors can also be handled effectively, and the interpretation of the binary tree is also intuitive. The model output is represented as a tree that is split according to threshold values of the variables that are considered to be significant contributors to the crises.

ANN method, although popular and predominantly used in the fields of science and engineering, has received relatively little attention in economics and finance. For debt crisis
prediction, Fioramanti (2008) uses the ANN method and the results show that the ANN model outperforms traditional logistic regression under certain conditions. The flexibility of the ANN and its ability to approximate non-linear relationships are considered the major advantages of this model.

This study applies a penalized logistic regression to estimate parameters of the external debt crisis (Firth, 1993). The rationale behind applying the penalized regression model lies in the small number of observations recorded (42 observations between 1970 and 2012) and the resultant separation problem, whereby one or more variables perfectly predict external debt crises from the standard logistic regression. The penalized regression model effectively solves these problems. In the penalized regression model, the log likelihood is maximized subject to a penalty that is dependent on the magnitude of the estimated parameters. A penalty on the log likelihood will penalize models that have large regression coefficients.

2.3 Penalized Logistic Regression

Logistic regression provides a robust classification method by modeling the probability of membership of a class with linear combinations of explanatory variables. However, a standard logistic regression may not work when there are more variables than actual observations. Two typical problems that might occur are multicollinearity and over-fitting. Here, one possible solution is to apply penalized logistic regression. Consider a standard linear regression model, as expressed in equation (2.1).

\[ Y = X\beta + \varepsilon \]  

(2.1)
In this case, $Y$ is a $n \times 1$ vector of dependent variables; $X$ is a $n \times m$ matrix of explanatory variables; $\beta$ is a $m \times 1$ vector of parameters; and $\varepsilon$ is a $n \times 1$ vector of errors. The regression coefficients are estimated by minimizing $S$ as follows:

$$S = \frac{1}{n} \sum_{i=1}^{n} (y_i - \sum_{j=1}^{m} x_{ij} \beta_j)^2$$  \hspace{1cm} (2.2)

This leads to the following:

$$\hat{\beta} = (X'X)^{-1}X'Y$$  \hspace{1cm} (2.3)

A large $m$ may lead to a problematic over-fitting. For a moderate number of variables (less than 15 covariates), it is generally required that the number of observations, $n$, is at least five times the number of covariates. Another problem is a perfect fit to the data (not in bias but high variance), and this can be misleading because large variability in the estimates produces a prediction formula for discrimination with almost no power (Antoniadis, 2007).

The main idea in penalization methods is to avoid overfitting by imposing a penalty on large fluctuations in the estimated parameters:

$$S_n(\beta) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \sum_{j=1}^{m} x_{ij} \beta_j)^2 + \lambda J(\beta)$$  \hspace{1cm} (2.4)

where $J(\beta)$ is a penalty that discourages high values of the elements of $\beta$. In generalized logistic regression, the logistic regression formula is expressed in equation (2.5):

$$y_i = \frac{p_i}{1-p_i} = \alpha + \sum_{j=1}^{m} x_{ij} \beta_j$$  \hspace{1cm} (2.5)
where \( y \) is the linear predictor function. Then, 
\[
\ell(y, \beta) = \sum_{i=1}^{n} y_i \log(p_i) + \sum_{i=1}^{n} (1 - y_i) \log(1 - p_i)
\]
is the log likelihood and 
\[
-\ell + \frac{\lambda}{2} J(\beta)
\]
is the penalized negative log-likelihood.

Firth (1993) introduces an algorithm of penalized regression to address issues of separability, small sample sizes, and bias of the estimated parameter. In the logistic regression, when the outcome has low (or high) prevalence, or when there are several interacted categorical covariates, all the observations can have the same event status. A similar event occurs when continuous covariates predict the outcome too perfectly. This phenomenon is known as the separation problem (including complete and quasi-complete separation) and will cause problems by over-fitting the model. Sometimes the only symptom of separation is due to unusually large standard errors, while in other cases, the statistical software may also report an error or a warning. When the sample size is large enough, the unconditional estimates and the Firth penalized-likelihood estimates should be nearly the same. Heinze and Schemper (2002) provide a more detailed analysis of separable data sets.

Consider the following logistic regression model:

\[
P(y_i = 1|x_i, \beta) = \pi_i = \{1 + \exp(-\sum_{r=1}^{k} x_{ir} \beta_r)\}^{-1}
\]  

(2.6)

Here, \((y_i, x_i), y_i \epsilon \{0,1\}, i = 1,2 \ldots n\) denotes a sample of observations of dependent variable \( y \) and a vector of independent variables with dimensions \( 1 \times k \). Maximum likelihood estimates for the regression parameter, intercept, and slopes, \( \beta_r, r = 1,2 \ldots k \), are found by solving the following \( k \) score equations:

\[
\frac{\partial \log(\ell)}{\partial \beta_r} = U(\beta_r) = 0
\]  

(2.7)
$L$ represents the likelihood function. To reduce the sample bias of these estimates, Firth (1993) suggests the estimation of a modified score equation, as expressed in equation (2.8):

$$U(\beta_r)^* = U(\beta_r) + \frac{1}{2} \text{trace}[I(\beta)^{-1}(\partial I(\beta)/\partial \beta_r)] = 0 \ (r=1,\ldots, k) \quad (2.8)$$

In this, $I(\beta)^{-1}$ is the inverse of the transformation matrix evaluated at $\beta$. The modified score function, $U(\beta_r)^*$, is related to the penalized log-likelihood and likelihood function, $\log L(\beta)^* = \log L(\beta) + \frac{1}{2} \log|I(\beta)|$, and $\log(\beta)^* = L(\beta)|I(\beta)|^{1/2}$, respectively.

STATA (version 12.0) is used to run penalized regression estimations, employing Firth’s penalized regression module. The separation problems and biased estimations are successfully solved using the Firth-type estimation, instead of the maximum likelihood estimation. The Firth logistic regression reduces the level of biased estimations if the separation problem occurs in the prediction of Indonesia’s external debt crises.

### 2.4 Data Description

The primary data sources for this analysis are the World Bank External Debt Statistics and the World Bank database. Important information on macro indicators that is not reported in the above publications is collected from the International Financial Statistics of the IMF. Data is compiled on the basis of 43 annual observations from 1970 to 2012.

The dependent variable, existence of external debt crises, is derived from data provided by the External Debt Statistics of the World Bank. An external debt crisis is defined as an event in which a country has large arrears in external obligations towards commercial creditors, or when a country has rescheduled or restructured their debt agreement with
commercial creditors.

Indonesia had large arrears in external debt from 1998 to 2004 and went on to reschedule or restructure external debt agreements from 1998 to 2005. Therefore, it is assumed that external debt crises in Indonesia occurred from 1998 to 2005. Since a crisis is a binary output variable, a crisis year is assigned as 1 and non-crisis is assigned 0. Table 2.1 presents the size of external debt and debt-to-GDP Indonesia from 1998 to 2005.

<table>
<thead>
<tr>
<th></th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td>Debt-to-GDP (%)</td>
<td>68</td>
<td>77</td>
<td>101</td>
<td>90</td>
<td>84</td>
<td>80</td>
<td>76</td>
<td>70</td>
</tr>
<tr>
<td>External debt (in million USD)</td>
<td>67</td>
<td>76</td>
<td>75</td>
<td>110</td>
<td>75</td>
<td>82</td>
<td>83</td>
<td>80</td>
</tr>
</tbody>
</table>

Source: CEIC database

The choice of covariates is largely drawn from existing literature. The theoretical literature highlights a variety of factors that can trigger a debt crisis, such as: a measure of debt solvency, i.e., debt-to-GDP ratio; debt liquidity, i.e., short-term debt-to-reserves or exports and debt service-to-reserves or exports; currency overvaluation; fiscal balance and other macroeconomic indicators, such as GDP growth and inflation (Manasse et al., 2003). Detragiache and Spilimbergo (2001) find that short-term debt, debt service and reserves are significant indicators that have high predictive power in relation to upcoming debt crises, while Ciarlone and Trebeschi (2005) use variables drawn from the debt sustainability measures including debt burden, debt service, reserves, macro indicators and net capital flows to explain external debt crises. Fioramanti (2008) uses macro indicators (GDP growth, inflation, interest rate, and currency overvaluation) and debt measures (short-term external debt, interest on external debt, total external debt, and average debt maturity) in his EWS
external debt crisis model.

This study uses various indicators from the EWS literature to form a foundation for predicting external debt crises (Table 2.2). The first variable (x1) is the average debt maturity. The debt maturity is the number of years to the original maturity date, which is the sum of grace and repayment periods. The grace period for the principal is the period from the date of signature of the loan, or the issue of the financial instrument, to the first repayment of the principal. The repayment period is the period from the first to the last repayment on the principal. To obtain the average, the debt maturity for all public and publicly guaranteed debt has been weighted by the amounts of the debt. When a country has a debt structure in which a large portion of its debt matures in the short-term, it is likely the country will have difficulty servicing this debt.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>Average maturity on new external debt commitments (years)</td>
</tr>
<tr>
<td>x2</td>
<td>Interest payments on external debt (% of exports of goods, services and primary income)</td>
</tr>
<tr>
<td>x3</td>
<td>Interest payments on external debt (% of GNI)</td>
</tr>
<tr>
<td>x4</td>
<td>Short-term debt (% of total external debt)</td>
</tr>
<tr>
<td>x5</td>
<td>Total debt service (% of exports of goods, services and primary income)</td>
</tr>
<tr>
<td>x6</td>
<td>Total reserves (% of total external debt)</td>
</tr>
<tr>
<td>x7</td>
<td>Central government debt, total (% of GDP)</td>
</tr>
<tr>
<td>x8</td>
<td>Public debt (% of GDP)</td>
</tr>
<tr>
<td>x9</td>
<td>Exports of goods and services (% of GDP)</td>
</tr>
<tr>
<td>x10</td>
<td>Inflation, consumer prices (annual percentage)</td>
</tr>
<tr>
<td>x11</td>
<td>GDP growth (annual percentage)</td>
</tr>
<tr>
<td>x12</td>
<td>Real interest rate (annual percentage)</td>
</tr>
<tr>
<td>x13</td>
<td>Domestic credit to private sector (% of GDP)</td>
</tr>
<tr>
<td>x14</td>
<td>Money and quasi money growth (annual percentage)</td>
</tr>
<tr>
<td>x15</td>
<td>Cash surplus/deficit (% of GDP)</td>
</tr>
</tbody>
</table>

Two other important variables are interest payments on external debt relative to exports of goods, services and primary income (x2) and interest payments on external debt
relative to gross national income (x3). The total interest payment is the sum of interest paid in currency, goods or services on long-term debt, interest paid on short-term debt and charges to the IMF. When a country has a relatively high portion of interest payments relative to exports, most export revenues will be allocated to debt repayment, thus weakening the country’s financial position.

Short-term debt as a percentage of total external debt (x4) can be used to indicate the problem of increased illiquidity and insolvency of a country in the short-run. The main reason for including this indicator is that in many instances of the debt crisis, short-term debt has increased significantly in the lead-up to the crisis. Short-term debt includes all debts with a maturity of one year or less. Total external debt is debt owed to non-residents, repayable in currency, goods or services. Total external debt is the sum of public, publicly guaranteed and private nonguaranteed long-term debt, IMF credit and short-term debt.

Total debt service relative to exports of goods and services (x5) measures the debt-servicing obligation of a country and can be a useful indicator in predicting a debt crisis. This is consistent with the view that some recent debt crises are experienced alongside liquidity and insolvency problems. The total debt service is the sum of principal repayments and interest paid in currency, goods or services on long-term debt, interest paid on short-term debt and repayments (repurchases and charges) to the IMF.

Total reserves to total external debt (x6) is an indicator which measures the extent to which foreign reserves are available to service debt. In times of crisis, stocks of foreign reserves are generally low due to the weaker balance of payments. A lower ratio of foreign reserves-to-GDP is an indication that the country may find it difficult to service its debt. Total foreign reserves comprise of holdings of monetary gold, Special Drawing Rights (SDR), reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities.
The ratio of central government debt to GDP (x7) and the ratio of public debt to GDP (x8) are other variables of interest. A high ratio of either central government debt-to-GDP or public debt-to-GDP can indicate that the debt level may be problematic and impact upon a country’s ability to repay its debt. Central government debt is the entire stock of outstanding government fixed-term contractual obligations to others on a particular date, and includes domestic and foreign liabilities, such as currency and money deposits, securities other than shares, and loans. It is the gross amount of government liabilities reduced by the amount of equity and financial derivatives held by the government. Public debt denotes the cumulative total of all government borrowings, less repayments that are denominated in a country's home currency.

For most developing countries, the basic source of funds for servicing their debts is the foreign exchange generated by exports of goods and services. Therefore, it is considered that ratio of exports of goods and services relative to GDP (x9) is a useful indicator to be included into the EWS model. It is also reasonable to assume that a high proportion of exports relative to GDP makes it less likely that a country has a large arrears or a need to reschedule or restructure on their debts. In other words, a high proportion of exports of goods and services will increase foreign exchange earnings and reserves capacity for servicing debt obligations. The domestic indicator of inflation (x10), annual GDP growth (x11) and the real interest rate (x12) are relevant variables that are widely used in EWS literature. Many developing countries have experienced high inflation episodes in the recent years, and if high inflation is present, part of the amortization of a loan will be transferred in the form of higher interest. There is also another channel through which inflation may affect the availability of foreign exchange. As domestic prices increase in times of high inflation, this reduces a country’s competitiveness and simultaneously reduces exports. Foreign reserves are depleted, resulting in either large debt arrears or debt rescheduling/restructuring. GDP growth is
relevant to the model because in times of strong GDP growth, the expansion of goods and services produced domestically can increase aggregate demand. In this situation, the supply of goods and services exports should potentially increase, while the demand for imports declines. The current account and balance of payment position should grow stronger, which is beneficial to a country’s ability to service its debt. A strong GDP growth may also contribute to the occurrence of external debt crises through the channel that the expansion of goods and services needs more investment, both domestic and foreign. This requires more financing in terms of higher domestic and external debts. The real interest rate indicates the extent to which a country is vulnerable to the increases of interest rates charged by private creditors, especially banks. In times of high positive real interest rates, higher rates would result in increased debt payment obligations. In such cases, debtor countries may be compelled to ask for debt rescheduling.

Domestic credit to the private sector relative to GDP (x13) refers to the financial resources provided to the private sector by financial institutions. In times of economic boom, there is a high level of domestic credit to the private sector relative to GDP. A very high level of domestic credit could be unsustainable and counterproductive if it creates overheating in the economy that could trigger a crisis.

The change in money supply (x14) is measured as the difference in end-of-year total M2 relative to the level of the preceding year. Money and quasi money (M2) encapsulates the sum of currency outside banks, demand deposits other than those of the central government, and the time, savings, and foreign currency deposits of resident sectors other than the central government. This indicator is associated with GDP growth and inflation. If money supply growth is rapidly outpacing economic growth, it will trigger higher inflation due to increased prices of goods and services. If inflation prevails, domestic prices increase and will eventually reduce exports and competitiveness. This will cause a deterioration of the
balance of payments and adversely impact debt servicing.

The fiscal indicator of cash surplus or deficit as a percentage of GDP (x15) provides a useful indication of a government’s need to turn to financial markets to meet its budget obligations. A country with a high cash surplus is less likely to raise debt or borrow money from the financial market. A cash surplus or cash deficit is revenue (including grants) minus the values for expenses and net acquisition of non-financial assets.

Famili et al. (1997) suggest to pre-process data before any data analysis process can start. This study pre-processes data by rescaling all original variables using the normalization and standardization methods. The objective of this data rescaling is to eliminate the difference in magnitudes that may affect the robustness of the results. The rescaling is important when dealing with parameters of different units and scales, as it ensures all parameters have the same scale, providing a fair comparison between them.

Normalization scales all numeric variables into the range [0,1], following the formula given below:

\[
x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}
\]

(2.9)

For standardization, all data are transformed to have a zero mean and unit variance. The formula for standardization is:

\[
x_{new} = \frac{x - \mu}{\sigma}
\]

(2.10)

As original variables have different units and scales, normalization and standardization are thus adopted. Normalization provides an advantage in handling data sets
with outliers, and standardization is more appropriate for data with normal distribution characteristics.

2.5 Analysis of Results

2.5.1 Event Study Analysis

The event study analysis is not only to provide some understanding of the behaviour of covariates around the time of crisis\(^3\), but also to investigate the direction and magnitude of selected indicators including average maturity of new external debt, interest payment, debt service, foreign reserves, central government debt, GDP growth, domestic credit and budget deficit prior to and during the debt crisis. Specifically, the aim of this event study analysis is to capture the response of those indicators when debt crisis is occurred and this method will be applied to measure these effects.

The results of the event study are shown in Figure 2.1. The dashed black horizontal line represents the average value during non-crisis periods, while the solid blue line shows the average value of the variable during crisis time, with a 95 percent confidence interval represented by the dotted lines. The period ranges from \(t-3\) to \(t+3\), where \(t\) is the year in which the external debt crisis occurs (\(y=1\)), thus signaling a crisis entry. A three-year crisis window is chosen as it sufficiently describes the behavior of each indicator around the debt crisis.

\(^3\) The event study figures are performed through regression of the respective explanatory variables on a set of dummy variables for the three years preceding the crisis (crisis entry), the crisis itself, and the three years following the crisis (crisis exit). The estimated constant is the mean of all non-default episodes, shown as the dashed horizontal line. The estimated coefficient on the dummies provides the difference from the non-default episode mean to the respective event (crisis entry or exit). Therefore, the mean for the respective event episode is computed by adding the estimated constant and the estimated coefficient on the dummy. The confidence interval indicates whether mean of the event is significantly different from the non-crisis means is computed from the confidence interval around the estimated event episode dummies by adding the lower and upper bound of the confidence interval to the estimated constant. The graphical representation of the test shows whether the coefficients on the dummies are significantly different from zero; and thus whether the means of the event episodes are significantly different from the non-crisis mean (Manasse et al., 2003).
crisis. For example, for other types of crisis, such as a balance-of-payments crisis, windows are defined as 24 months preceding and following the crisis, while a banking crisis window is defined as 12 months before and after the crisis (Kaminsky and Reinhart, 1999).
Entry

Average maturity on new external debt commitment (years)

Interest payments on external debt (% of exports of goods, services and primary income)

Interest payment on external debt (%GNI)

Exit

Average maturity on new external debt commitment (years)

Interest payments on external debt (% of exports of goods, services and primary income)

Interest payment on external debt (%GNI)
The event study suggests that measures of external debt are significantly different during crisis periods with respect to non-crisis periods. In the year preceding the crisis, some debt measures such as interest payments, short-term debt, debt maturity, debt service and central government debt are higher than their average value during normal times. In the year following the crisis (exit), these indicators are moderated toward their historical averages.

There is a significant decrease in the GDP growth in the year prior to crisis, suggesting that GDP growth can be considered as one of the main indicators in predicting future crises. Inflation also rose significantly in the year before the crisis. The event study results confirm studies of (Manasse et al., 2003; Ciarlone and Trebeschi, 2005).
2.5.2 Principal Component Analysis

This study applies Principal Component Analysis (PCA), which is used to detect whether certain underlying patterns of relationships exist among covariates. In the PCA, some covariates can be reduced into a set of principal components, which is less than the number of original covariates. The PCA helps to explain as much information regarding the original covariates as possible, by extracting linear combinations of original covariates into some composite indicators. The robust PCA should retain most information from the original covariates and simplify the covariates. As study’s observations are limited, the PCA helps to reduce the dimension of parameters and thus increase the degree of freedom in the model. The principal component can be expressed as equation (2.11) below:

\[ x_{i,k} = a_{i1}C_1 + a_{i2}C_2 + \cdots + a_{ik}C_k, \]  

(2.11)

Here, each of the \( n \) observed variables \( (x_i) \) are described as the linear combination of the \( k \) components, \( C_1, C_2, \ldots, C_k \); and \( a_{ik} \) is the factor loading (regression weight) on the \( k^{th} \) component.

The first component maximizes the variance, while the subsequent components account for the entire variance. The most important components are those which have higher contributions to the total variance and usually have eigenvalues greater than 1.0, while components with eigenvalues less than 1.0 only explain a small portion of the variance.

The components are extracted in a way which ensures that one component is independent of the others, i.e., components are orthogonal, and the loadings of such
components are referred to as un-rotated components. To obtain terminal solutions, the un-rotated components are rotated by maximizing the variance of the squared loadings. This study uses variance of orthogonal rotation (varimax) method.

The original 15 variables are reduced into several principal components and in doing so retained most information from the original variables. Scenario analysis using different numbers of principal components are also conducted and then compared in terms of the level of total variance explained by each component.

This study uses the Kaiser-Meyer-Olkin (KMO) and Bartlett’s test to measure sampling adequacy. The Bartlett test of sphericity compares the correlation matrix with a matrix of zero correlations (identity matrix). This test shows a small $p$-value, indicating that it is highly unlikely that the observed correlation matrix is a matrix with zero correlation. The results show an associated $p$-value of 0 and thus the null hypothesis is rejected. Applying the normalization and standardization rescaling method, the KMO value is 0.539, greater than the suggested value of 0.5.

Table 2.3 shows the cumulative percentage of variance explained by different numbers of principal components. The higher numbers of principal components explain more variation, as opposed to the lower numbers of principal components. For example, seven principal components could explain about 98 percent of the variation of the variables, while four components only explain 88 percent of the variation.

<table>
<thead>
<tr>
<th>Rescaling method</th>
<th># Principal components</th>
<th>% Cumulative variance explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalization/Standardization</td>
<td>4</td>
<td>88.28</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>93.33</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>96.32</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>98.06</td>
</tr>
</tbody>
</table>
The component matrix is rotated using varimax rotation (an orthogonal rotation with Kaiser Normalization) to obtain optimal solutions. The variables with a correlation less than 0.4 are removed, as this study only selects on variables with high correlation.

Regarding the rotation matrix, the top variables with a variance greater than 0.85 for each component are selected. The following variables are selected as the most significant variables for the first component: interest payment on external debt, total debt service and reserves to external debt. For the second component, inflation, GDP growth, and the real interest rate are the most meaningful indicators. The third component is represented by public debt-to-GDP and the fourth component by average debt maturity, while the fifth component is represented by central government debt-to-GDP (see Table 2.4).

Table 2.4 Principal Component and Factor Loading

<table>
<thead>
<tr>
<th>Variable</th>
<th>Component</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#1</td>
</tr>
<tr>
<td>x1</td>
<td></td>
</tr>
<tr>
<td>x2</td>
<td>0.953</td>
</tr>
<tr>
<td>x3</td>
<td>0.712</td>
</tr>
<tr>
<td>x4</td>
<td>0.565</td>
</tr>
<tr>
<td>x5</td>
<td>0.970</td>
</tr>
<tr>
<td>x6</td>
<td>-0.904</td>
</tr>
<tr>
<td>x7</td>
<td></td>
</tr>
<tr>
<td>x8</td>
<td></td>
</tr>
<tr>
<td>x9</td>
<td></td>
</tr>
<tr>
<td>x10</td>
<td></td>
</tr>
<tr>
<td>x11</td>
<td></td>
</tr>
<tr>
<td>x12</td>
<td></td>
</tr>
<tr>
<td>x13</td>
<td>0.668</td>
</tr>
<tr>
<td>x14</td>
<td></td>
</tr>
<tr>
<td>x15</td>
<td>0.231</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations
As some components have high factor loadings that explain most variance such as average debt maturity, internal payments on external debt, total debt service, reserves to external debt, central government debt to GDP, public debt to GDP, inflation, GDP growth and the real interest rate, it is argued that they are the most meaningful indicators which enable prediction of the occurrence of debt crises (see Table 2.5).

### Table 2.5 Indicators with High Predictive Power of Debt Crises

<table>
<thead>
<tr>
<th>Variable</th>
<th>Indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>Average maturity on new external debt commitments (years)</td>
</tr>
<tr>
<td>x2</td>
<td>Interest payments on external debt (% of exports of goods, services and primary income)</td>
</tr>
<tr>
<td>x5</td>
<td>Total debt service (% of exports of goods, services and primary income)</td>
</tr>
<tr>
<td>x6</td>
<td>Total reserves (% of total external debt)</td>
</tr>
<tr>
<td>x7</td>
<td>Central government debt, total (% of GDP)</td>
</tr>
<tr>
<td>x8</td>
<td>Public debt (% of GDP)</td>
</tr>
<tr>
<td>x10</td>
<td>Inflation, consumer prices (annual percentage)</td>
</tr>
<tr>
<td>x11</td>
<td>GDP growth (annual percentage)</td>
</tr>
<tr>
<td>x12</td>
<td>Real interest rate (annual percentage)</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

The findings of this study confirm the findings of (Manasse et al., 2003; Ciarlone and Trebeschi, 2005). Ciarlone and Trebeschi (2005) find that interest payments on external debt more than double in the year preceding the crisis and became increasingly large in the crisis year. The short-term external debt increases in the period preceding an entry into debt crisis and is significantly higher in the year before the entry of the crisis than it is in non-crisis episodes (Manasse et al., 2003; Ciarlone and Trebeschi, 2005). The level of foreign reserves also changes significantly during crisis periods as opposed to tranquil times, with the level of foreign reserves as a percentage of total external debt dropping significantly in the year
preceding a crisis year (Ciarlone and Trebeschi, 2005). Real GDP growth also falls below its average prior to a crisis, while inflation rises significantly in the year preceding the crisis (Manasse et al., 2003; Ciarlone and Trebeschi, 2005).

Table 2.6 shows the results of the standard logistic regression model. Using a standard logistic regression model with 15 original covariates, the results suggest that separation problem occurs and the estimated parameters are biased. The PCA helps to reduce the dimension of parameters and thus increases the degree of freedom of the model. The results from Table 2.5 suggest that PCA with 1 and 2 principal components eliminate a separation problem, even though its results are not significant. The estimated parameters are biased and separation problems occur. Firth (1993) addresses this separation problem using a technique called the penalized maximum likelihood algorithm. This method reduces the level of biased estimations and large standard errors of the parameters.

<table>
<thead>
<tr>
<th>Data set</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>15 original variables</td>
<td>Separation occurs (x8* predicts crisis perfectly)</td>
</tr>
<tr>
<td>15 variables normalized</td>
<td>Separation occurs (x8* predicts crisis perfectly)</td>
</tr>
<tr>
<td>15 variables standardized</td>
<td>Separation occurs (x8* predicts crisis perfectly)</td>
</tr>
<tr>
<td>9 variables normalized (as defined in Table 2.4)</td>
<td>Separation occurs (x8* predicts crisis perfectly)</td>
</tr>
<tr>
<td>9 variables standardized (as defined in Table 2.4)</td>
<td>Separation occurs (x8* predicts crisis perfectly)</td>
</tr>
<tr>
<td>4 variables (GDP growth and inflation, money growth and real interest rate)</td>
<td>No separation problem, but no variable is significant at 5 percent</td>
</tr>
<tr>
<td>2 variables (GDP growth and inflation)</td>
<td>GDP growth is significant at 5 percent</td>
</tr>
<tr>
<td>PCA: 1 Component</td>
<td>C1 is not significant</td>
</tr>
<tr>
<td>PCA: 2 Components</td>
<td>C1 and C2 are not significant</td>
</tr>
<tr>
<td>PCA: 3 Components</td>
<td>Separation occurs (C3** predicts crisis perfectly)</td>
</tr>
<tr>
<td>PCA: 4 Components</td>
<td>Separation occurs (C3** predicts crisis perfectly)</td>
</tr>
<tr>
<td>PCA: 5 Components</td>
<td>Separation occurs (C3** predicts crisis perfectly)</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations
Notes: *x8 is the ratio of public debt-to-GDP.

2.5.3 Penalized Logistic Regression

The results of the penalized likelihood estimation are presented in Table 2.7. At the 5 percent significance level, GDP growth is a significant indicator for debt crises. The probability of a debt crisis increases by 63 percent when annual GDP growth falls by 1 percent. Using the principal components, with a 1 percent increase in the ratio of public debt-to-GDP (Component 3), the probability of a debt crisis increases by 78-81 percent. This confirms the findings of (Rogoff and Reinhart, 2010), who assert that countries with high ratio of debt-to-GDP (90 percent or above, i.e., including Indonesia) in times of crisis, tend to experience markedly lower growth outcomes and significantly higher levels of inflation. During the debt crisis, Indonesia’s inflation rises dramatically from about 7 percent a year prior to the crisis, to as high as 58 percent in the crisis year. In the aftermath of the crisis, GDP growth and inflation returns to a more moderate level. One possible explanation for this is that the process of debt leveraging had already taken place. This also confirms Rogoff and Reinhart (2010), which concludes that debt leveraging is a process whereby there is a sharp reduction in external debt, resulting in lower growth and a slowdown in the economy.
Table 2.7 Firth Penalized Regression

<table>
<thead>
<tr>
<th>Data sets</th>
<th>Wald statistics</th>
<th>P &gt; Chi-square</th>
<th>Odds ratio</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>15 original variables</td>
<td>9.32</td>
<td>0.86</td>
<td>-</td>
<td>No variable is significant</td>
</tr>
<tr>
<td>15 variables normalized</td>
<td>9.32</td>
<td>0.86</td>
<td>-</td>
<td>No variable is significant</td>
</tr>
<tr>
<td>15 variables standardized</td>
<td>9.32</td>
<td>0.86</td>
<td>-</td>
<td>No variable is significant</td>
</tr>
<tr>
<td>9 variables normalized (as defined in Table 4)</td>
<td>7.82</td>
<td>0.65</td>
<td>-</td>
<td>No variable is significant</td>
</tr>
<tr>
<td>9 variables standardized (as defined in Table 4)</td>
<td>7.82</td>
<td>0.65</td>
<td>-</td>
<td>No variable is significant</td>
</tr>
<tr>
<td>4 variables (GDP growth, inflation, money growth and real interest rate)</td>
<td>3.11</td>
<td>0.54</td>
<td>-</td>
<td>No variable is significant</td>
</tr>
<tr>
<td>2 variables (GDP growth and inflation)</td>
<td>3.74</td>
<td>0.15</td>
<td>0.63 (GDP growth)</td>
<td>GDP growth is significant at 5 percent</td>
</tr>
<tr>
<td>PCA: 1 Component</td>
<td>0.41</td>
<td>0.52</td>
<td>-</td>
<td>C1 is not significant</td>
</tr>
<tr>
<td>PCA: 2 Components</td>
<td>2.37</td>
<td>0.31</td>
<td>-</td>
<td>C1 and C2 are not significant</td>
</tr>
<tr>
<td>PCA: 3 Components</td>
<td>5.78</td>
<td>0.12</td>
<td>0.78 (C3)</td>
<td>C3 is significant</td>
</tr>
<tr>
<td>PCA: 4 Components</td>
<td>6.73</td>
<td>0.15</td>
<td>0.80 (C3)</td>
<td>C3 is significant</td>
</tr>
<tr>
<td>PCA: 5 Components</td>
<td>6.40</td>
<td>0.27</td>
<td>0.81 (C3)</td>
<td>C3 is significant</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

2.6 Conclusion

This study uses Firth’s penalized logistic regression to examine Indonesia’s external debt crisis. The penalized regression method has been used effectively to solve the separation problem resulting from a standard logistic regression, where one variable of a public debt-to-GDP ratio perfectly predicts an external debt crisis. The penalized regression model shows that GDP growth and the public debt-to-GDP ratio are among the most significant indicators in the prediction of an external debt crisis. With a 1 percent decrease in annual GDP growth,
the probability of an external debt crisis occurring increases by 63 percent, while a 1 percent increase in the public debt-to-GDP ratio will increase the probability of a debt crisis by about 80 percent. This confirms the findings of (Rogoff and Reinhart, 2010) that, in emerging market economies, a high level of debt is associated with lower growth outcomes and a significantly higher level of inflation.
3.1 Introduction

The calamity of the 1998 Asian financial crisis had a devastating impact on the Indonesian economy. Indonesia plummeted into its debt crisis that has led to a visible deterioration in living standards, as well as increased unemployment in the country. In 1998, Indonesia is without an EWS to anticipate an impending debt crisis. The purpose of an EWS is to provide critical data indicators for the likelihood of a coming financial crisis. These indicators cover a series of crisis variables, linked with currency, housing markets, stock, and debt markets. EWS effectively monitors early indicators of crises, so as to trigger an immediate response and influence the course of action. Research also shows that the EWS (and the critical response that results) are extremely effective in mitigating risk and predicting financial crises (Edison, 2000; Fioramanti, 2008; Pan et al., 2010).

This study sets out to develop an EWS for Indonesia’s external debt crises, using the Artificial Neural Network (ANN) approach to determine whether an external debt crisis in Indonesia can be predicted. Research regarding EWS, and Indonesia’s external debt crises in particular, has been minimal. There is a line of literature on the use of EWS relating to Indonesia’s currency crises (Syafidullah, 2012; Tambunan, 2002). However, there are no previous works investigating EWS for predicting Indonesia’s external debt crises. The main advantage of the ANN is its ability to implicitly detect complex, non-linear relationships
between the predictor and dependent variables (Tu, 1996). There exist numerous economic indicators can be used to signal external debt crises. However, relationships between variables are sometimes difficult to understand. If a significant amount of non-linearities exist between macroeconomic variables and the corresponding occurrence of debt crises, the ANN will automatically assign a greater weight to its structure to reflect these non-linearities. Empirical studies also suggest that when complex, non-linear relationships exist in the data sets, the ANN model is not only able to achieve a greater fit and aggregate forecasting than a standard regression model, but is also capable of capturing a non-linear relationship between independent and dependent variables (Pao, 2008).

The remainder of this chapter is organized as follows: Section 3.2 provides a review of the literature, Section 3.3 describes the ANN model specification, Section 3.4 describes the ANN model architecture for external debt crises prediction, Section 3.5 presents the empirical results and Section 3.6 concludes.

3.2 Literature Review

In recent years, many empirical studies have added a great deal to the research and development of models in predicting the occurrence of financial crises. Two central approaches that have been adopted are parametric and non-parametric models. The parametric approach includes a logistic model (Eichengreen and Rose, 1999), while the non-parametric approach includes a signal model (Kaminsky et al., 1998). The logistic model uses limited dependent variables of a probit or logit model to test the statistical significance and usefulness of certain variables as indicators of the occurrence of a financial crisis. In the signal model, various leading indicators are selected, and then threshold values for a crisis
signal are determined. These threshold values are determined within the sample, given statistical significance, and then are tested for their out-of-sample performance.

Previous research into the usefulness of the EWS in predicting a financial crisis focuses primarily on developing countries (Frankel and Rose, 1996; Berg and Pattillo, 1999a; Kaminsky and Reinhart, 1999). Current research also includes developed countries to better reflect the wider scale of recent financial crises (Barrell et al., 2010; Babecký et al., 2013). Research shows that certain countries have promptly adopted an EWS specifically for financial crises, such as South Korea (Kim et al., 2004a), Romania (Albulescu, 2010), and Turkey (Ari, 2012).

Earlier studies on the EWS focus almost exclusively on currency crises (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999). In recent literature, EWS has been developed to cover different types of crises, including banking crises (Barrell et al., 2010; Oet et al., 2013), housing market crises (Davis and Karim, 2008; Dreger and Kholodilin, 2013) and debt crises (Manasse et al., 2003; Ciarlone and Trebeschi, 2005; Fioramanti, 2008; Fuertes and Kalotychou, 2007; Hong and Yuan-Cheng, 2010; Bucevska, 2011).

The number of studies of EWS on external debt crises is small when compared to the empirical and theoretical works regarding other types of crises (Babecký et al., 2013). Many papers mainly focus on EWS for sovereign debt crises in developing countries (Schmidt, 1984; Berg and Pattillo, 1999b; Manasse et al., 2003; Ciarlone and Trebeschi, 2005; Fioramanti, 2008; Fuertes and Kalotychou, 2007; Hong and Yuan-Cheng, 2010). Nonetheless, the recent studies of the EWS for debt crises have also extended to developed economies and OECD countries (Babecký et al., 2013).

Manasse et al. (2003) provide one of the earliest studies predicting external debt
crises. They employ a variety of methods to assess the role of macroeconomic fundamentals in increasing risks of sovereign default, and trigerring a debt crisis, across a broad sample of countries. Empirical evidence suggests that a number of macroeconomic factors can predict the probability of an impending national debt crisis. Debt measures, such as a high level of foreign debt, may increase the likelihood of the debt default. Furthermore, a large debt service is another meaningful indicator for predicting a debt crisis. Low GDP growth, current account imbalances, low trade openness, tight liquidity, high inflation, and a high ratio of public debt to GDP are all indicators which also carry strong predictive power in relation to debt crises.

In particular, Manasse et al. (2003) employ event study analysis to observe the behavior of variables around the time of crisis. The results of their study show that total external debt and the ratio of public debt to GDP both significantly rise in the lead-up to a crisis. Prior to a crisis, short-term debt relative to reserves also increases to a level significantly higher than in non-crisis periods. Debt servicing and interest payments relative to reserves also tend to increase compared to non-crisis times. Current account deficits appear higher before entry into an actual crisis, while foreign reserves plummet in the years before the crisis. GDP growth decreases significantly in the entry year of the crisis, while inflation rises substantially. At the time of exit from the crisis, most indicators return to their normal level. Manasse et al. (2003) develop EWS based on the logistic regression and recursive tree model. The logistic model predicts 74 percent of entries into a crisis while producing few false alarms. In comparison, their recursive tree model correctly predicts 89 percent of entries into a crisis, although it creates more false alarms.

Ciarlone and Trebeschi (2005) develop EWS for debt crises based on the multinomial model. This method distinguishes three phases of debt crises: a tranquil phase, a crisis phase, and a post-crisis phase. They use a set of 28 macroeconomic indicators in a debt crisis model,
with indicators drawn from the literature on debt sustainability (which measures the burden of debt, debt service, foreign reserves, monetary indicators, and net capital flows). Their models are able to successfully predict 76 percent of entries into crisis, while causing false alarms 35 percent of the time. They also employ event study analysis to monitor the behaviour of variables before and after debt crises. The results of the event study suggest that measures of external debt service are significantly higher during a crisis as compared with non-crisis periods. Interest payments on external debt are more than double their usual level in the year prior to a crisis. The total debt service, including principal payments, is significantly higher than during non-crisis periods, and the ratio of external debt-to-GDP also increases considerably in the run-up to a crisis. Foreign reserves drop significantly during crisis periods, while short-term debt relative to reserves increases substantially in the year preceding a crisis.

Fuertes and Kalotychou (2007) use 24 indicators in their EWS models, sourced from five categories of the World Bank data classification, including external credit exposure, external economic activity and financial resources, domestic indicators, international financial links, and global indicators. Their analysis is based on annual data from 1983 to 2002, across 96 developing economies. The results of the study suggest that a parsimonious logistic model produces the most accurate forecast of sovereign default. The observable indicators that have good predictive power for debt crises include the following: trade-to-GDP, external debt-to-GDP, official debt-to-total debt, IMF credit-to-exports, and credit to the private sector-to-GDP.

A more recent approach towards predicting debt crises has been using data mining method of the ANN. Earlier attempts to adopt ANN is to predict financial crises include those by Nag and Mitra, 1999; Fioramanti, 2008). Nag and Mitra (1999) use an ANN to construct an EWS for currency crises prediction in Malaysia, Thailand, and Indonesia, and compared
the results with the signal approach. The results show that the ANN model performs better than the signal approach, specifically in the out-of-sample predictions. In his study, Fioramanti (2008) finds that in-sample prediction performance of the ANN achieves exceptional results, correctly predicting 95.79 percent of non-crisis and 91.30 percent of crisis episodes. Considering the out-of-sample prediction, the results show that ANN also has a high degree of prediction power with low Type 1 error.

Although the ANN seems to have a superior fit compared to the linear time series model, it has several disadvantages (Sekmen and Kurkcu, 2014). The ANN is considered to be a “black-box” model, and it is somewhat difficult to interpret the parameters. Another weakness of the ANN is the problem of over-fitting, particularly on the training data sets. With the flexibility of the ANN model, it is possible to obtain a near perfect fit in the in-sample predictions, but the model may perform poorly in the out-of-sample predictions.

3.3 ANN Model Specification

In terms of model specification, the ANN is largely depending on the relevant inputs that are independent variables (in regression term), output of activation function and number of nodes in the activation function. Even though the ANN requires no knowledge of the data source, but it contains many weights that must be estimated, so it requires large training sets. The output activation function can be a linear or non-linear equation in \( H \) the hidden layer. The linear form is usually used in ANN modelling because the nodes are usually nonlinear. If there are two \( H \) functions; the linear output function can be written as follows:

\[
Y = B_0 + H_1B_1 + ... + H_nB_n + u
\]  

(3.1)
In terms of $H$, the output function, Equation (3.1) is the linear multiple regression with $n$ independent variables. We may not know the optimal number of nodes to be included until the training (estimation) stage.

The hidden $H$ function can be either linear or nonlinear. This study uses nonlinear cumulative logistic distribution function, which is the same form as the Logit model. The logistic curve is a S-shaped sigmoid. Using $X_n$ input variable, the logistic function $H_n$ is as follows:

$$H_n = \frac{1}{1+e^{-(b_0+b_1x_1+\ldots+b_nx_n)}}$$ (3.2)

The ANN is a flexible, non-linear modeling tool that has an ability to develop a system, which can learn from training examples. In other words, the ANN uses the examples to automatically infer rules for predicting or recognizing patterns. The major advantage of using ANN is its ability to capture a non-linear relationship between explanatory variables and dependent variables. In earlier years, ANN models are predominantly used in engineering, but recently more attention has been given to applications in the fields of business and economics. ANN models are mainly used in business and economics fields to address forecasting and classification problems. For example, Kim et al. (2004a) and Kim et al. (2004b) apply a BP neural network model to predict economic crisis in South Korea, while Yu et al. (2006) use a neural network to predict the currency crisis in Southeast Asia using currency volatility indicators. Similarly, Celik and Karatepe (2007) use a feedforward neural network model for forecasting banking crises, while Son et al. (2009) and Lin et al. (2008) adopt a fuzzy expert system of the EWS for predicting financial crises.

The ANN model imitates a biological neural network. The model is inspired by the
working of the human brain in terms of using a neuron and synaptic connection structure in processing data, and also being able to learn from past experience (predictive programming).

The ANN is a non-linear, statistical data modeling tool and is usually used to model complex relationships between inputs and outputs, as well as identify patterns of data. It consists of a simple three-layer structure, which performs three basic functions: receiving signals (inputs), processing these signals, and sending them to the output neurons. External information, corresponding to independent variables, is received in the first layer, called the input layer. Each neuron in the input layer then sends signals to what is called the hidden layer, and this information is then processed. In statistics, the output layer corresponds to a dependent variable.

3.4 The ANN Model Architecture

The ANN model is a layered structure with neurons in each of three different layers (Figure 3.1), known as the input, hidden, and output layers. The first layer (input layer) consists of a set of explanatory variables with one bias neuron usually added. The purpose of adding a bias neuron in the input layer is to help the ANN model learn the patterns. A bias neuron is a neuron that has a constant output of one. As bias neurons have this constant output of one and are not connected to the previous layer, adding a bias allows the neurons to learn a threshold value. The bias terms can be interpreted as additional weights. The neurons of the input layer are passive, that is, they cannot modify the data. They receive a single value of their inputs and duplicate the value to their multiple outputs. All neurons in each layer are connected to other neurons in the next layer but there is no connection between neurons within the same layer.
Each value from the input layer is sent to a second, hidden layer. The values entering neurons in the hidden layer are multiplied by weights, a set of predetermined numbers. The weighted inputs are then added to produce a single composite number. Before leaving the neurons, this number is passed through an activation function. For example, a sigmoid activation function limits the neuron output so that it can only be between 0 and 1, while the input value could be between $-\infty$ and $+\infty$. As opposed to the passive neurons in the input layer, all neurons in the hidden layer and output are active as they can modify data.

![Figure 3.1 Architecture of the ANN model](image)

The outputs from the hidden layer are then transmitted to the next layer; the output layer. The active nodes of the output layer combine and modify the data to produce the output values of the network.

### 3.4.1 Input Layer

The first step in developing the ANN model is to define appropriate indicators for the input
The variables in the input layer can, theoretically, be as many as possible, although it is necessary to select an appropriate subset of variables from a set of measured potential input variables when using data-driven models such as the ANN (Fernando et al., 2005). In the case of high dimensional data sets, selecting a subset of potential input variables is necessary to reduce the number of free parameters in the model and to obtain useful generalization with finite data. The performance of the final model is also heavily dependent on the input variables. The correct choice of model inputs is therefore important for improving computational efficiency.

May et al. (2011) argue that in the case of ANN, or other similar data-driven statistical modeling approaches, input variables are largely selected from the available data and the model should be developed afterward. The difficulty with selecting input variables for the ANN model is attributed to several factors. For example, when there are a large number of input variables available, high correlations between input variables which can create redundancy, or variables with little or no predictive power. The advent of ANN models with inherent non-linearity, complexity, and non-parametricity makes it difficult to apply many of the existing analytical variable selection methods. The difficulty of selecting input variables is further exacerbated during the ANN development process, since the ANN model is capable of identifying redundant and noise variables during training, and the trained network uses only the most salient input variables.

The decision to choose the size of input variables is also important as it may critically affect the final output. Some studies show that using fewer input variables is a superior strategy as opposed to using too many input variables, as the noise of the data sets degrades the performance of the ANN model (Walczak and Cerpa, 1999; Yu et al., 2006). On the other hand, Jain and Nag (1995) find that using an exhaustive list of input neurons can improve the performance of the ANN. Also, Walczak and Cerpa (1999) suggest removing variables that
are particularly noisy or correlated with other variables in order to avoid performance degradation.

3.4.2 Hidden Layer

The hidden layer in the ANN model connects the input and output layers. There are two decisions that must be made with respect to hidden layers: (i) how many hidden layers to use, and (ii) how many neurons to use in each of these layers. The ANN model with one hidden layer can approximate any function that contains continuous mapping from one finite space to another. However, a model with two hidden layers can approximate any smooth mapping with a higher degree of accuracy. There is no theoretical evidence for using neural networks with more than two hidden layers to improve forecasting accuracy. In the case of many practical problems, one or two hidden layers are most commonly used in the ANN model.

The choice of the number of neurons in the hidden layers is essential and must be carefully considered as it could have a critical impact on the overall performance of the ANN. A small number of neurons in the hidden layers will result in under-fitting. Under-fitting occurs when the number of neurons in the hidden layers is inadequate for the purpose of detecting signals in a complex data set. On the other hand, using too many neurons in the hidden layers can cause several problems. Firstly, the existence of too many neurons in the hidden layers may result in over-fitting. Over-fitting occurs when the error in the training set is driven to a very small value, yet when new data is presented to the network, the error is large. In this case, the ANN has memorized the training examples, but it has not learned to generalize to the new situations. A large number of neurons in the hidden layers can also increase the processing time required to train the network. Therefore, deciding the number of
neurons in the hidden layers requires a balance. There are various ways to determine the optimal number of neurons. One possibility is to set the number of neurons in the hidden layer to be somewhere between the size of the input layer and the size of the output layer. Another option is to set the number of hidden neurons to be less than twice the size of the input layer.

### 3.4.3 Output Layer

The final layer in the ANN model is the output layer. The output neuron in the output layer represents the predicted variable. In this study, there is only one expected output, that is, the probability of external debt crises with a value of either 0, in the case of non-crisis, or 1 in the event of a crisis. As the output is a binary variable and the output neuron reflects the probability of external debt crises with value between 0 and 1, a logistic activation function is applied.

### 3.4.4 Learning Algorithm

This study uses the ANN Back-Propagation (BP) algorithm, a supervised learning algorithm. Wong et al. (2000) find that 95 percent of the business applications of neural networks use the BP algorithm. The BP algorithm consists of multi-layer perceptrons, and each iteration involves a forward stage and a backward stage. In the forward stage, the output value is calculated using the weights and output values of the previous layer, while in the backward stage, weights are computed using the errors and output value of the next layer. According to Hong and Yuan-Cheng (2010), training a neural network using the BP algorithm involves
several steps:

[1]. Randomly initialize the weight and bias of BP neurons. The weight could be from -1 to 1.

[2]. Calculate the output value in each layer. The output value of the input layer is equal to the input value. The output value, \( O_j \), of the hidden layer and the output layer is:

\[
O_j = f(\sum_i w_{ij} O_i + O_j)
\]

where \( w_{ij} \) is the weight between neuron \( i \) and neuron \( j \) in neighbor layers; \( O_j \) is the bias of neuron \( j \), and function \( f \) may adopt the logistic function of:

\[
f(x) = \frac{1}{1+\exp(-x)}.
\]

[3]. Calculate the error. Neuron \( k \) in the output layer has an error value of \( E_k \)

\[
E_k = O_k (1 - O_k) (y_k - O_k)
\]

where \( O_k \) is the real output value of neuron \( k \), and \( y_k \) is the expected value of neuron \( k \).

[4]. Backpropagate new weights and biases. Weights and biases are updated using the following formula:

\[
w_{ij} = w_{ij} + \eta E_j O_i
\]

\[
O_j = O_j + \eta E_j
\]

Where \( \eta \) is the learning rate and we set \( \eta = 0.3 \).

[5]. Evaluate training performance. Mean Squared Error is calculated as follows:

\[
E = \frac{1}{2} \sum (O_k - y_k)^2
\]

When error value, \( E \), is smaller than a given value, or the loop number is larger than a given value, training stops. Otherwise, iterations continue until a desired output value
is achieved.

### 3.4.5 The Prediction Power of the ANN

To determine the prediction power and performance of the ANN, the error percentage metrics are used both for in-sample and out-of-sample prediction and thus there are no statistical tests involved. The metrics used include Type 1 error (false positive) when a crisis is incorrectly identified as a non-crisis and Type 2 error (false negative) when a non-crisis is incorrectly called a crisis. Other error metrics include mean absolute error and root mean squared error.

The performance of the ANN model is measured by looking primarily at the out-of-sample total misspecification error (TME), amongst other error metrics such as the percentage of crisis episodes correctly called, the percentage of non-crisis episodes correctly called, the percentage of missed crises and the percentage of false alarms. The TME is computed as the sum of Type 1 errors and Type 2 errors.

\[
TME = \text{Type 1 errors} + \text{Type 2 errors}, 
\]

(3.8)

Where:

\[
\text{Type 1 errors} = \frac{\text{Total missed crisis episodes}}{\text{Total crisis episodes}} 
\]

(3.9)

\[
\text{Type 2 errors} = \frac{\text{Total false alarms}}{\text{Total non-crisis episodes}} 
\]

(3.10)
3.5 ANN Model for External Debt Crises

To build the ANN model for external debt crisis prediction, several steps must be followed. The first step is to determine the output neuron. The second stage involves selecting input variables for the input neuron and then determining the number of hidden layers and hidden neurons. It is also important to decide on the type of activation function, the number of iterations, the learning rate and the momentum rate.

In this study, the output neuron is the external debt crisis in Indonesia. This study follows the definition of external debt crises as occurring when there are large arrears on external obligations of more than five percent of the total debt stocks (Detragiache and Spilimbergo, 2001; Kraay and Nehru, 2006; Ciarlone and Trebeschi, 2005; De Paoli et al., 2006; Cohen and Valadier, 2010), or when an agreement is rescheduled or restructured into less favourable terms for the lenders than in the original arrangement (Chambers and Alexeeva, 2003; Ciarlone and Trebeschi, 2005; Rogoff and Reinhart, 2010). Indonesia has had large arrears on their external debts over the period 1998 to 2004. Indonesia has also rescheduled/restructures their external debt agreements from 1998 to 2005. Thus, it is assumed that Indonesia has experienced external debt crisis from 1998 to 2005.

The next stage is to select the set of variables for the input neurons, in order to ensure the accuracy of the output prediction. The selection of input variables is important and has a tremendous influence on the final output as in (Zhang et al. 1998; Walczak and Cerpa, 1999). The choice of input variables is largely driven by the literature. As most developing countries, including Indonesia, largely rely on export earnings to repay foreign loans (Mundial, 2012), several factors related to export earnings are included as input variables. During the debt crisis, the increase in external debt stocks generally outpaces the rise in export earnings, and this is usually followed by a sharp depreciation of the domestic currency.
against the US dollar. The depreciation of domestic currency magnifies the debt service, as much of the foreign loans are denominated in US dollar. To service the debt, the nearest source of debt repayment is foreign reserves. There is considerable empirical evidence suggesting that foreign reserves deteriorate in times of external debt crises.

This study uses five input variables that are considered to have a significant impact on the occurrence of an external debt crisis: exports, imports, the exchange rate, foreign reserves and foreign debt repayments including principal and interest (Table 3.1). The choice of input variables is largely driven by the literature. As Indonesia largely relies on export earnings to repay foreign loans, export and import indicators are thus included as one independent variable. During the debt crisis, an increase in external debt stocks generally outpaces the rise in export earnings, and this is usually followed by a sharp depreciation of the domestic currency against the US dollar. The depreciation of domestic currency magnifies the debt service, as much of the foreign loans are denominated in US dollar. Therefore exchange rate is also used as an input variable. To service the debt, the nearest source of debt repayment is foreign reserves. There is also considerable empirical evidence suggesting that foreign reserves deteriorate in times of external debt crises.

**Table 3.1 Input Variables**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>Foreign reserves (nominal value in USD)</td>
</tr>
<tr>
<td>x2</td>
<td>Exports (annual percentage change)</td>
</tr>
<tr>
<td>x3</td>
<td>Imports (annual percentage change)</td>
</tr>
<tr>
<td>x4</td>
<td>Exchange rate (IDR/USD)</td>
</tr>
<tr>
<td>x5</td>
<td>Foreign debt repayments including principal and interest (nominal value in USD)</td>
</tr>
</tbody>
</table>

The existence of correlated input variables can potentially increase the noise that leads to decreased performance of the ANN. Table 3.2 shows that there is low correlation amongst input variables, and thus they can be used for the model.
Table 3.2 Correlation Matrix

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Foreign reserves</th>
<th>Exports</th>
<th>Imports</th>
<th>Exchange rate</th>
<th>Foreign debt repayments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foreign reserves</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exports</td>
<td>0.28</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imports</td>
<td>0.12</td>
<td>-0.10</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.15</td>
<td>0.22</td>
<td>0.10</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Foreign debt repayments</td>
<td>0.17</td>
<td>0.01</td>
<td>-0.04</td>
<td>0.13</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

Since the dimensions of each input variable vary, natural logarithm of foreign reserves, the exchange rate, and foreign debt repayments are taken to provide equal proportional contributions and to remove biases in the forecasting model. The export and import variables are already in annual percentage terms.

The next step is to define the number of hidden layers and the number of neurons in the hidden layers. Some scholars argue that one hidden layer is sufficient to solve most problems (Yu et al., 2006), but this study also tests with two hidden layers to observe whether an additional hidden layer can improve the overall performance of the model. The choice of the number of neurons in the hidden layers can be problematic. A higher number of neurons can lead to an over-fitting problem, while too few neurons can result in the decreased ability of the model to capture a complex and non-linear relationship between the data sets. There is no set agreement on the optimal number of neurons for each hidden layer. As previously discussed, one could argue that the number of neurons in the hidden layers should be between the size of the input layer and output layer, or alternatively that the number of hidden neurons should be less than twice the size of the input layer.

This study applies the network pruning method to trim the network size in order to improve computational and prediction performance, as suggested by Augasta and
Kathirvalavakumar (2011). This approach removes neurons from the hidden layers during the training process by identifying those neurons which, if removed from the network, would not noticeably affect network performance. Various numbers of hidden neurons are used and the optimal number of hidden neurons are chosen at the point where the model has the smallest error. The findings suggest that the smallest training error is reached when the number of hidden neurons is equal to the number of input variables. This agrees with (Syaifullah, 2012) who finds that the optimal number of hidden neurons equals to the number of input variables. This study also confirms the findings from (Karsoliya, 2012), that prediction accuracy of the neural network model can be improved without sacrificing the complexity of the network, by increasing the number of hidden layers up to three layers. Furthermore, there is no need to increase the number of neurons or layers, as this will lead to over-fitting.

The logistic activation function is used in the ANN model. As the output neuron in the model is the probability of crisis, with value between 0 and 1, the logistic activation function thus ensures that the output of the model is within this range. For consistency, the logistic activation function is also used in the hidden neurons. Apart from the learning algorithm, there are some other factors that can contribute to overall ANN model performance. The learning rate, momentum, and number of iterations are considered to be important factors that have a major influence on the overall ANN model performance. The learning rate is the training parameter that controls the size of weight and bias changes in the learning of the training algorithm. If the learning rate is set to a large value, the ANN may learn more quickly, but if there is large variability in the input set, the network may not learn very well. The learning rate is usually set to a low value, which may be increased when the learning rate is too slow. This study sets the initial learning rate at 0.3, and this results in a root mean squared error of 21.97 percent. This study also tests the ANN model with a higher learning rate of 0.4 and 0.5, and finds that the root mean squared error increases to 22.33 percent and
22.93 percent, respectively.

The momentum parameter is used to prevent the system from converging to a local minimum. A high momentum parameter can also help increase the speed of convergence of the system; however, setting the momentum parameter too high can create a risk of overshooting the minimum. Conversely, a momentum coefficient that is too low cannot reliably avoid local minima and can also slow down the training process. As suggested in the literature, the initial momentum rate is first set at 0.2 and produces a root mean square error of 21.97 percent. A higher momentum rate of 0.3 and 0.4 are also used, generating root mean squared error of 21.39 and 22.01 percent, respectively. This study, therefore, uses momentum rate of 0.3 with the least value of the root mean squared error.

When training multi-layer networks, data sets are divided into three subsets. The first subset is the training set or in-sample test, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on this validation set is monitored during the training process. The validation error normally decreases during the initial phase of training. The network weights and biases are saved at the minimum of the validation set error. The third subset is the test set or out-of-sample set.

As there are in total 228 observations from January 1995 to December 2013, the data set is partitioned into three subsets, allocating 70 percent for training sets, 15 percent for the validation sets, and the remaining 15 percent for the test sets. The data sets are also split into different combinations in order to minimize the root mean squared error (Table 3.3). Table 3.3 shows that the optimal ANN structure is reached with the following proportions: 60 percent training data sets, 20 percent validation data sets, and 20 percent test sets (with minimum root mean squared error at 23.06 percent)
Table 3.3 Data Partition

<table>
<thead>
<tr>
<th>Model</th>
<th>Training set (%)</th>
<th>Validation set (%)</th>
<th>Test set (%)</th>
<th>Root mean squared error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>29.12</td>
</tr>
<tr>
<td>#2</td>
<td>60</td>
<td>20</td>
<td>20</td>
<td>23.06</td>
</tr>
<tr>
<td>#3</td>
<td>70</td>
<td>15</td>
<td>15</td>
<td>30.08</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

Using training parameters of learning and momentum rates, the ANN model sets the initial connection weights between neurons and bias neurons in the input layer to the neurons in the hidden layer. The signals propagate forwards from the input to hidden layer and eventually to the output layer. The input neurons are transformed by the logistic activation function into a value range between 0 and 1, and then all the signals and bias are summed into one composite value in the hidden layer. Subsequently, in the hidden layer, the ANN model sets another initial connection weight between hidden neurons and output neurons, and a similar process is applied. All these signals are then summed using the logistic activation function to arrive at one composite output value. Table 3.4 shows the configuration of the ANN model.

Table 3.4 ANN Configuration

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of network</td>
<td>Multi-layer perceptrons</td>
</tr>
<tr>
<td>Training algorithm</td>
<td>BP</td>
</tr>
<tr>
<td>Number of hidden layers</td>
<td>1</td>
</tr>
<tr>
<td>Number of neurons in the hidden layer</td>
<td>5</td>
</tr>
<tr>
<td>Number of neurons in the output layer</td>
<td>1</td>
</tr>
<tr>
<td>Activation function</td>
<td>Logistic</td>
</tr>
<tr>
<td>Performance function</td>
<td>Mean squared error</td>
</tr>
<tr>
<td>Starting weight</td>
<td>Random</td>
</tr>
<tr>
<td>Number of iterations</td>
<td>10,000</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.3</td>
</tr>
<tr>
<td>Momentum</td>
<td>0.3</td>
</tr>
</tbody>
</table>
The neural network starts the learning process by comparing the output neuron with the desired target. The error is then transferred in a backward direction from the output layer to the input layer, via the hidden layer, using the BP algorithm. This learning process will determine the appropriate connection weights between neurons with the final objective of reaching a minimum error. This study sets a maximum number of iterations at 10,000 iterations. There is no specific rule for determining the maximum number of iterations, although the number of iterations must be large enough for the model to achieve convergence. The ANN model stops the learning process whenever the model reaches the maximum number of iterations or produces the minimum root mean squared error. The results show that the minimum root mean squared error of the model is 23.06 percent.

The ANN model can produce information regarding the relative contribution of each input neuron to the output neurons. This can be considered similar to the estimated coefficient in the classic regression model. Table 3.5 shows the relative contribution of input neurons to the output in the ANN model. The most significant input variables in the model are the exchange rate (44.5 percent), followed by foreign reserves (35 percent) and exports (17 percent).

<table>
<thead>
<tr>
<th>No.</th>
<th>Description</th>
<th>(%) contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Foreign reserves</td>
<td>35%</td>
</tr>
<tr>
<td>2</td>
<td>Exports</td>
<td>17%</td>
</tr>
<tr>
<td>3</td>
<td>Imports</td>
<td>1.4%</td>
</tr>
<tr>
<td>4</td>
<td>Exchange rate</td>
<td>44.5%</td>
</tr>
<tr>
<td>5</td>
<td>Foreign debt repayments</td>
<td>2.2%</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations
3.6 Empirical Results

3.6.1 In-Sample Performance

Table 3.6 shows the ANN model performance in terms of error percentages. There are two types of errors: false positive (Type 1 error) and false negative (Type 2 error). False positive error takes place when a crisis is incorrectly identified as a non-crisis, while false negative error occurs when a non-crisis is incorrectly called a crisis. A false positive error is more severe than a false negative error due to the high costs associated with a crisis. Overall, the findings show that the ANN model can correctly classify all crisis and non-crisis episodes reasonably well (92.98 percent success rate). The false positive rate is 10.78 percent (that is, the model has a 10.78 percent error rate in identifying a crisis as a non-crisis), while the false negative rate is 3.96 percent (classifying a non-crisis as a crisis). The confusion matrix provides more information on the performance of the ANN model (Table 3.7). In the in-sample prediction, the model can correctly predict a crisis with 89.21 percent degree accuracy, and it correctly predicts a non-crisis 96.03 percent of the time.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean absolute error</td>
<td>12.45</td>
</tr>
<tr>
<td>Root mean squared error</td>
<td>23.02</td>
</tr>
<tr>
<td>Correctly Classified Instances</td>
<td>92.98</td>
</tr>
<tr>
<td>Incorrectly Classified Instances</td>
<td>7.02</td>
</tr>
<tr>
<td>False positive rate</td>
<td>10.78</td>
</tr>
<tr>
<td>False negative rate</td>
<td>3.96</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations
Table 3.7 In-Sample Confusion Matrix

<table>
<thead>
<tr>
<th>Actual class</th>
<th>Predicted class</th>
<th>Non-crisis</th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-crisis</td>
<td></td>
<td>121</td>
<td>11</td>
</tr>
<tr>
<td>Crisis</td>
<td></td>
<td>5</td>
<td>91</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

As policymakers are more concerned with Type 1 errors (preferring to have fewer false positive error than false negative error) due to the high costs associated with incorrectly predicting crises, this ANN model can be used for the prediction of the external debt crises in Indonesia.

3.6.2 Out-of-Sample Performance

To test the ability and robustness of the ANN model in predicting external debt crises, this study simulates out-of-sample prediction with the training and validation data set ranging from May 2008 to December 2013 (40 percent of all samples). The ANN model is then evaluated in terms of its ability to predict external debt crisis in Indonesia, based on different error metrics (Table 3.8).

Table 3.8 Out-of-Sample Error Percentages

<table>
<thead>
<tr>
<th>Description</th>
<th>Value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean absolute error</td>
<td>11.38</td>
</tr>
<tr>
<td>Root mean squared error</td>
<td>23.06</td>
</tr>
<tr>
<td>Correctly Classified Instances</td>
<td>90.11</td>
</tr>
<tr>
<td>Incorrectly Classified Instances</td>
<td>9.89</td>
</tr>
<tr>
<td>False positive rate</td>
<td>14.28</td>
</tr>
<tr>
<td>False negative rate</td>
<td>7.14</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations
The out-of-sample model sends more false signals than the in-sample model, as indicated by the higher percentage of false positives (14.28 percent) and false negatives (7.14 percent). It suggests that the ANN model tends to over-fit the data in the in-sample, but it cannot fit the out-of-sample very well. To address this concern, one solution is to increase the size of observations, as this will effectively mitigate the over-fitting problem in the ANN model.

Table 3.9 Out-of-Sample Confusion Matrix

<table>
<thead>
<tr>
<th>Actual class</th>
<th>Predicted class</th>
<th>Non-crisis</th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-crisis</td>
<td>Non-crisis</td>
<td>52</td>
<td>5</td>
</tr>
<tr>
<td>Crisis</td>
<td>Non-crisis</td>
<td>4</td>
<td>30</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

This study also uses out-of-sample experiments with $k$-fold cross-validation technique to evaluate out-of-sample performance and see how well a model generalizes beyond the original training samples. The advantages of using $k$-fold cross-validation, rather than data sets partitioned into training and test sets, are that all data observations are used for both training and test sets, and each observation is used for the test exactly once. In the $k$-fold cross-validation, the original samples are randomly partitioned into $k$ equal size subsamples. The cross-validation process is then repeated $k$ times (folds), with each of the $k$ subsamples being used exactly once as the validation data. The $k$ results from the folds are then averaged to produce a single estimation. The 10-fold cross-validation is commonly used in a neural network model (McLachlan et al., 2005). The out-of-sample error of 10-fold cross-validation is presented in Table 3.10. The results show that the ANN model can predict the occurrence of external debt crises effectively, with a lower false positive rate (8.69 percent) and false negative rate (8.82 percent), and is capable of correctly identifying crisis episodes with 91.30
percent accuracy. Table 3.11 presents the confusion matrix.

Table 3.10 Out-of-Sample Error Percentages with 10-Fold Cross-Validation

<table>
<thead>
<tr>
<th>Description</th>
<th>Value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean absolute error</td>
<td>13.68</td>
</tr>
<tr>
<td>Root mean squared error</td>
<td>25.51</td>
</tr>
<tr>
<td>Correctly Classified Instances</td>
<td>91.23</td>
</tr>
<tr>
<td>Incorrectly Classified Instances</td>
<td>8.77</td>
</tr>
<tr>
<td>False positive rate</td>
<td>8.69</td>
</tr>
<tr>
<td>False negative rate</td>
<td>8.82</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

Table 3.11 Confusion Matrix for Out-of-Sample Prediction with 10-Fold Cross-Validation

<table>
<thead>
<tr>
<th>Actual class</th>
<th>Predicted class</th>
<th>Non-crisis</th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-crisis</td>
<td>Non-crisis</td>
<td>124</td>
<td>8</td>
</tr>
<tr>
<td>Crisis</td>
<td>Crisis</td>
<td>12</td>
<td>84</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

3.6.3 Performance Evaluation

To assess the ANN model’s in-sample performance, the procedure is as follows. First, the training samples are set from January 1995 to April 2006, which is about 60 percent of all samples. The validation sets are allocated 20 percent, while the remaining 20 percent are for the test set. Table 3.12 shows that the accuracy of out-of-sample performance is lower than the in-sample performance, as reflected by the higher out-of-sample TME scores (24.17 percent), Type 1 error (14.28 percent) and Type 2 error (9.89 percent). The 10-fold cross-validation improves the out-of-sample prediction with a lower TME (17.46 percent), Type 1 error (8.69 percent) and Type 2 error (8.77 percent).
Table 3.12 In-Sample and Out-of-Sample Performances

<table>
<thead>
<tr>
<th>Sample windows</th>
<th>Crisis episodes correctly called (%)</th>
<th>Non-crisis episodes correctly called (%)</th>
<th>Type 1 error (%)</th>
<th>Type 2 error (%)</th>
<th>TME (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-sample:</td>
<td>89.21</td>
<td>96.03</td>
<td>10.78</td>
<td>7.01</td>
<td>17.79</td>
</tr>
<tr>
<td>Out-of-sample</td>
<td>85.71</td>
<td>92.86</td>
<td>14.28</td>
<td>9.89</td>
<td>24.17</td>
</tr>
<tr>
<td>10-fold cross-validation</td>
<td>91.30</td>
<td>91.18</td>
<td>8.69</td>
<td>8.77</td>
<td>17.46</td>
</tr>
</tbody>
</table>

Source: Author’s own calculations

The findings of the study confirm that the EWS can help to identify past crisis episodes with a fairly high degree of accuracy for in-sample performance. However, predicting crisis episodes outside the estimation samples is much more challenging due to the presence of uncertainty.

3.7 Conclusion

This study examines the performance of the ANN model with a BP algorithm in correctly predicting in-sample and out-of-sample external debt crises in Indonesia. The results suggest that the exchange rate, foreign reserves and exports have a significant contribution to the outbreak of an external debt crisis. On the other hand, imports and foreign debt repayments are not major factors leading to external debt crises in Indonesia. In the in-sample prediction, the ANN model can correctly classify crises 89.12 percent of the time. However, the performance of the out-of-sample prediction is not as good as the in-sample prediction. It is argued that the ANN model tends to over-fit the data in the in-sample, while it cannot fit the out-of-sample very well. Using 10-fold cross-validation, it improves out-of-sample prediction accuracy and the performance of the ANN model also increases substantially. These results
suggest some policy implications. The ANN model can be used to identify past crisis episodes with a high degree of accuracy. However, predicting crises outside of the estimation sample proves a greater challenge due to the uncertainty that may be present.
Chapter 4 UNDERSTANDING INDONESIA’S CREDIT CYCLES

4.1 Introduction

Credit cycles are integral components of the banking system across the globe. In essence, a credit cycle is a sequence involving the access to credit by borrowers. In times of credit expansion, credit cycles start to occur when funds are easy to borrow. During these periods, lending standards may loosen, and excessive leverage and asset price bubbles follow. Credit expansions end with credit contractions and crises. During these periods, the interest rate increases and lending rules become stricter, reducing credit in the economy. These periods continue until risks are reduced, at which point the cycle starts again.

Indonesia has witnessed credit cycles over time. Rapid overexpansion of credit in Indonesia in recent years can be explained by several factors including a stable macroeconomic environment, financial deepening, availability of new lending instruments, and robust economic growth (IMF, 2015). The country is still in its developmental phase, and as such, credit tends to grow at a faster pace than output. Such a situation is not limited to Indonesia; some developed nations also experienced faster credit growth than output due to financial liberalization (Aikman et al., 2015). As Indonesia’s development goals involve more pronounced economic growth, financial deepening and rapid credit growth have become evident (Elekdag and Wu, 2011). Whilst rapid credit growth is associated with excessive credit expansions, at the end of credit boom, it will eventually be followed by credit contractions. In Indonesia, a major credit boom occurred before the 1997 Asian
Financial Crisis (AFC) and the 2009 Global Financial Crisis (GFC); subsequently, credit busts have followed these booms. During the credit bust after the AFC, the value of the Rupiah significantly dropped against the USD triggering the replacement of a managed floating exchange rate regime by a free-floating exchange system (Bartoletto et al., 2015). These credit busts are also accompanied by an acute economic recession that led to the contraction of Indonesia’s GDP by more than nine percent. Prior to the GFC, Indonesia experienced credit overexpansion, which is amplified by prolonged low interest rate regimes and loose bank lending practices, specifically in the consumer and property sector. Soon after the GFC, a credit bust occurred and the value of Rupiah against the USD depreciated significantly by more than 20 percent, while GDP dropped by about 1.5 percent.

This study presents some empirical evidence of the characteristics of credit cycles in Indonesia, including credit booms and busts. More importantly, this study will also examine specific characteristics of sub-components of credit such as working capital, investment and consumption credit. The determinants of credit booms will also be investigated. The rest of this chapter starts with the discussion of credit situation in Indonesia in Section 4.2. This is followed by a review of literature in Section 4.3., and the analytical framework which is presented in Section 4.4, including definitions of credit gaps, credit booms and busts, credit cycles, cycle co-movement and the empirical strategy for determining factors of credit booms. Empirical results are presented in Section 4.5, and Section 4.6 concludes.

4.2 Credit Sector in Indonesia

The credit sector in Indonesia has enjoyed unprecedented high growth in recent years. The Financial Services Authority (OJK), which is the Indonesian government agency that
regulates and supervises the country's financial services sector, reported that average annual credit growth in Indonesia has been impressive, at about 16.3 percent in the last 5 years from 2012 to 2016. In levels, the credit has grown from Rp1,702 Trillion in 2007 to Rp6,570 Trillion in 2016. This high growth rate has been largely driven by high accumulation of saving deposits and high lending capacity of the banking sector. The banking sector is able to attract deposits (third party funds) with relatively low cost of funds, and could disburse credits with quite a significant margin. The average cost of funds in Indonesia is about 6.49 percent, while the average loanable lending rate varies from 12.5 to 15.4 percent; thus the banking sector in Indonesia has had a lucrative net interest margin (NIM) in a regional context. Indonesia’s banking sector has an average NIM of 5.8 percent, which is the highest among ASEAN countries. For example, the average NIM in Singapore, Thailand, Malaysia and Philippines are 1.6 percent, 2.9 percent, 3 percent and 3.3 percent respectively.

In 2016, the OJK estimated credit growth to be only six to seven percent, a level that is well below its historical average. The slowing credit growth could be attributed to sluggish global and domestic economic growth, as well as the slow progress of government-led infrastructure projects. A tedious land acquisition process and lack of government fiscal guarantees contributed to many long delayed public infrastructure projects in Indonesia. To resolve this issue and accelerate the land acquisition process for public infrastructure projects, the government passed the following: the Land Acquisition Act in January 2012, Presidential Decree No. 71 of 2012 and Presidential Decree No. 30 of 2015. The aim of these policies is to facilitate private investment in the land acquisition process. According to Presidential Decree No. 71 (2012), land acquisition financing must be conducted through state owned enterprises (SOEs), a process which is usually fairly lengthy. Under the new decree, private sectors may involve and finance the procurement of land. The government has also
established the Viability Gap Funding (VGF), which facilitates government guarantees in an effort to speed up infrastructure developments.

In terms of credit disbursements by economic sectors, manufacturing and trade are responsible for about 51 percent of total credit in 2016. These shares are consistent with Indonesia’s GDP shares of these economic sectors. As components of Indonesia’s GDP, manufacturing and trade compose 20.8 and 13.3 percent respectively; hence, the two sectors contribute to more than 34 percent of Indonesia’s GDP. There has been high credit growth in the manufacturing sector due to strong demand in working capital credit, specifically in the consumer goods industry, while robust demands for export and import credits contributed to the trade sector. Other economic sectors that have had significant contributions to Indonesia’s GDP are: agriculture (13.4 percent), construction (10.2 percent), services (10 percent), and mining (8.2 percent). Even though the share of the agriculture sector has been significantly decreased in recent years, the agriculture sector is still the largest contributor to national employment, with more than 38 percent of the total labourers nationally.

The demand for working capital credit is responsible for 47 percent of total credit, followed by consumption credit (27.5 percent) and investment credit (25.5 percent). The large demand for working capital credit may be attributed to surging demand from small-to-medium enterprises (SMEs) and the growing number export-oriented firms. Trade, hotel and restaurant sectors are the largest contributors for working capital credit (20.4 percent), followed by the agriculture, livestock, forestry and fishery sector (17.1 percent) and the manufacturing sector (16.5 percent). With respect to investment credit, the high demand for credit in the construction, service and transportation sectors has contributed to strong growth. High demand for residential and vehicle credit contributed to robust growth in consumption credit. In 2016, residential credit accounted for 28.6 percent of total consumption credit, followed by vehicle credit of 10 percent.
As a result of rapid credit expansion in recent years, the Indonesian authority has introduced various measures to control growth. According to the 2016 Banking Survey of Bank Indonesia, it is expected that new loans in 2017 set to grow by 13.1 percent (y.o.y), up from 8.3 percent (y.o.y) in 2016, driven by solid liquidity in the banking industry, lower lending rates and sound domestic economic conditions. The Survey also reported that all types of new loans enjoyed stronger demand, predominantly on consumption credit (with WNB\(^4\) mounting from 26.8 to 72.8 percent), followed by working capital loans (WNB increased from 54.5 to 84.2 percent) and investment credit (WNB up from 68 to 69.9 percent). To control excessive growth in consumption credit, Bank Indonesia raised all three of the following: the loan-to-value ratio (LTV), financing-to-value ratio (FTV) on housing loans, and down payments on motor vehicle loans. These measures also aimed to limit speculation practices, whilst maintaining prudential principles. In addition, Bank Indonesia also imposed new regulations on banking and financial institutions that non-performing loans (NPL) should be less than five percent of total credits as stipulated in the Bank Indonesia Regulation (PBI) No. 18/16/PBI/2016. Bank Indonesia restricts credit card ownership based on monthly income criteria. Individuals with incomes of less than Rp3 million are prohibited from owning a credit card. Individuals with an income of between Rp3 million and Rp10 million are permitted to own credit cards from a maximum of two issuers, with a total credit limit of three times their monthly income. Individuals with an income of more than Rp10 million are not restricted in terms of credit card ownership but are subject to a risk analysis by each respective card issuer. With respect to working capital and investment credit, the central bank focused on raising the quality of credit provision, thereby maintaining the NPL

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\(^4\) WNB = Weighted Net Balance, a measure used in the Banking Survey of Bank Indonesia to indicate respondent’s response. It is calculated by multiplying respondent’s responses with its own credit share then calculated the difference between the percentage number of respondent answering “increase” and those who answer “decrease” and neglecting those who answer “the same”. The formula: WNB = % “weighted increasing” responses - % “weighted decreasing” responses
4.3 Review of Literature

Credit cycles play a pivotal role in explaining fluctuations in credit markets (Aikman et al., 2015). Fluctuations of credit include periods of credit expansion (boom) and credit contraction (bust). The credit boom phase of the cycle is characterised by large deviations in the level of credit above the trend, while credit busts are reflected by a large deviations below the trend. An excessive credit expansion or credit boom is a situation when credit experiences an unsustainably high growth, and will eventually collapse (credit bust). The excessive credit expansion may be the result of any number of factors, including herd behaviour (Kindleberger and O'Keefe, 2001), agency problems which lead to the implementation of loose lending policies (Petersen and Rajan, 1995), or a lack of economic policies (Calvo, 1986) to name a few. Booms and Are (2004) coin the term ‘financial accelerator’ as the main cause of a credit boom. They argue that the ‘financial accelerator’ may be a result of financial market imperfections such as information asymmetries, institutional shortcomings, or perverse incentives facing borrowers and lenders.

Booms and Are (2004) assert that credit can grow rapidly for three main reasons: 1) financial deepening; 2) normal cyclical upturns; and 3) excessive cyclical movements (credit booms). On financial deepening, it is noted that credit will typically grow faster than GDP as the economy develops. There is also a body of literature presenting evidence that more developed and advanced credit sectors are needed to help to boost economic growth (Marashdeh and Al-Malkawi, 2014; Best et al., 2017). While Marashdeh and Al-Malkawi (2014) find that financial deepening (measured by broad money supply M2 over GDP) has a
positive and statistically significant long-run impact on economic growth, there is no
evidence to suggest that there is a short-run dynamic bidirectional relationship between the
two variables. In the study Best et al. (2017), they suggest that both short and long-run
relationships existed between financial deepening and economic growth. Contrary to this
literature, Zanello and Padilla (2013) find a negative relationship between financial
deepening and economic growth. They argue that financial deepening does not always fulfil
its role in mobilising deposits into productive investments, showing that the relationship
between financial development and economic growth is not always positive.

Beyond financial deepening, credit may also experience a temporary rapid expansion
that exceeds GDP growth. For example, Indonesia is a country with a large proportion of
working capital credit (60 percent of total credit). Hence, the absorption of working capital
credit may much larger than output. However, credit and economic growth could move in the
opposite directions or with different magnitudes. These fluctuations are not unusual.

Following the GFC, there are discussions of global financial stability and the role of
the credit cycle in financial crises. The European Banking Federation argues that the study of
credit cycles is integral to the discovery of credit booms, which is a critical predictor for
financial crises (Calem et al., 2011). The Federation affirms that credit cycles are critical to
explain fluctuations in the business cycles. In addition, Peydró (2014) argues that regulatory
authorities, academics and policy-makers should pay close attention to credit cycles. He finds
that fluctuations of credit, including excessive credit growth, could lead to financial crises. In
summary, it is asserted that excessive credit growth may be due to a lack of market discipline,
deficient corporate governance, and/or poor macro-prudential policies.

It is of great importance to study credit series in order to comprehend the
fluctuations and behaviours of credit cycle (Drehmann et al., 2012; Borio, 2014). As distinct
from the business cycle (which has been well studied), the literature on the credit cycle is
relatively new and is yet to be thoroughly examined (Stremmel, 2015). There is also a
difference between business cycle and credit cycle. While the main focus of the business
cycle is to understand real economic activity or growth of real output (GDP) over the cycle,
credit cycle studies aim to comprehend the cyclicality of a credit series (Borio, 2014).

Credit cycles are a subset of financial cycles. The financial cycle comprises different
economic cycles such as credit, property, debt or stock markets. The credit cycle specifically
captures the evolution of a credit situation in a country through expansion (boom) and
contraction (bust) episodes. When credit is expanding, the supply of loanable funds is
abundant and more than sufficient to finance borrowing demands from investment and
household consumption. The result is higher economic output overall. On the other hand,
when loan and credit supply is squeezed, the real economy may slow down.

The study of credit cycles in Indonesia ties in well with the study of (Elekdag and Wu
2011) which presents the findings of a comprehensive study on credit cycles across both
advanced and emerging economies. They identified a credit boom (bust) when real credit is
above (below) its trend by 1.55 times the standard deviation. In their study, they argue that a
credit boom occurs when there is lack of prudent monetary policies, such as sustained low
policy rates and huge capital inflows. In addition, Shin and Shin (2011) argue that a relaxed
monetary policy gave financial institutions capacity to extend borrowing beyond its limit that
can lead to credit overexpansion. Cecchetti (2010) shows that a credit boom occurred when
there is a significant increase in credit lending that leads to credit overextension especially in
the private sector.

To understand credit cycles and fluctuations of credit in the economy, it is important
to study the credit gap. To examine the credit gap, some studies adopt credit-to-GDP ratio as
in (Gourinchas et al., 2001; Barajas et al., 2013). The credit-to-GDP ratio however, has a few
limitations. Firstly, it is possible that when both nominal credit and GDP are falling, but the
magnitude changes are different, which can result in misleading conclusions. Secondly, the credit-to-GDP ratio also does not allow for the possibility that credit and output might have different trends. Alessi and Detken (2014) identify that the best indicator to explain excessive credit growth is the credit gap at level. Some previous studies also document that a credit gap is among the first measures that can be used to indicate signs of credit overexpansion (Drehmann and Tsatsaronis, 2014). This study uses credit gap at level when constructing a credit cycle, following the study of (Mendoza and Terrones, 2008; Alessi and Detken, 2014; Drehmann and Tsatsaronis, 2014).

Several theories have been advanced with the intention of improving understanding of the short-term dynamics of credit cycles and their associations with real output fluctuations. The Hyman Minsky hypothesis of financial instability is particularly important in pioneering the idea that economic instability could be triggered by variations and fluctuations in credit cycles (Knell, 2015). Simply put, Minsky argues that a period of stability would trigger borrowers to borrow and lenders to be reckless, resulting in instability in the economy. Roubini (2007) also asserts that many economic bubbles, including credit bubbles, follow a typical Minsky hypothesis. Oppers (2002) proposes a different view on the credit cycles; he gives a version of Austrian Theory that relates credit cycles to business cycles and argues that the creation of credit by monetary institutions pushes investments beyond the community's long-term willingness to save, which may eventually lead to a recession due to a supply-demand incompatibility.

Drehmann et al. (2012) describe various methods of identifying and characterizing credit cycles. Their studies focus on two methods of frequency-based filter analysis and turning point analysis. The frequency-based filter analysis defines that the frequency range should be specified before doing the analysis (Che and Shinagawa, 2014), while the turning point method focuses on how a credit series behaves around the cycle (Baxter and King,
Each method has its own advantages and disadvantages. The frequency-based method has the advantage of preventing loss of oversight of short and medium term perspective, as it also considers the long-term horizon of the cycle. The main weakness of this method is that it may be biased toward the direction of the pre-determined threshold and range (Strohsal et al., 2015). Unlike the frequency-based filter method, the turning point method adopts some pre-specified rule that characterizes cycles by identifying the peak and trough of the cycle. This method’s main strength is its ability to compare short and medium term cycles, but the main weakness is that the peaks and troughs must be examined thoroughly, which makes renders the process highly tedious. Another method, a multivariate model, could also be used in the determination of the credit gap (Hosszú et al., 2015; Bezem and Zhang, 2014; Davis and Karim, 2008). The advantage of this method is that it allows one to examine the start and the end of the credit boom and bust, but the main shortcoming is that it requires a large amount of observations.

This study contributes to the existing empirical literature in a number of ways. Firstly, previous studies focus their analyses on the examination of credit cycle characteristics in advanced and developing market economies, while this study specifically focuses on Indonesia’s credit market. Secondly, this study attempts to examine determinants of the credit booms for a specific country, Indonesia, while many previous studies used cross-country comparisons. Thirdly, this study particularly differs from previous studies in terms of the use of data. Most empirical studies used low frequency data of annual observations, while this study adopts monthly observations that enable us to capture more dynamics of credit fluctuations in the country.
4.4 Analytical Framework

4.4.1 Credit Gap

The credit-to-GDP gap, the difference between the credit-to-GDP ratio and its long-term trend, has been widely used in many studies (Borio and Lowe, 2002). This indicator, however, has limitations. For example, Drehmann and Tsatsaronis (2014) criticize the use of the credit-to-GDP gap as it is not the best early warning indicator to describe fluctuations of a credit cycle, especially in the case of emerging market economies; and it also has measurement problems. They suggest that a combination of indicators, such as the credit-to-GDP gap, credit growth, GDP growth, residential property price growth, the debt service ratio (DSR) and the non-core liability ratio, be used instead. It is suggested these indicators would produce a more precise signal for early warning purpose. This study thus adopts the credit gap to measure fluctuations of a credit series around its long-term trend.

In order to compute the credit gap (cyclical component), firstly, the value of credit $C_t$, deflated by CPI in month $t$, is taken. The trend, $C_τ$, is then derived using the Hodrick-Prescott filter with a smoothing parameter of 14,400 for monthly observations, in accordance with the literature (Mise et al., 2005). The credit gap $C^{\text{gap}}_t$ is defined in the following equation (4.1):

$$Credit\ gap_t = C^{\text{gap}}_t = C_t - C_τ$$

(4.1)

4.4.2 Credit Boom and Bust

Bezemer and Zhang (2014) study a detailed description of the definition and measurement of credit boom and bust. They identify credit boom and bust episodes as a deviation from the
long-term trend. A credit boom occurs when the deviation of the real credit from its long-run trend is equal to or higher than a certain threshold. This study uses a threshold of 1.65 times the standard deviation of the cyclical component. The long-run trend is derived from the Hodrick-Prescott (HP) filter with the smoothing parameter set at 14,400, which is typical for monthly data. This study identifies a credit boom as follows. Let $\tilde{C}_t$ be the credit gap (cyclical component) of credit series $C_t$. If $\tilde{C}_t > 1.65\sigma_{\tilde{C}_t}$, where $\sigma$ is the standard deviation of the cyclical component, it is identified as a credit boom. The value of one is taken when credit boom occurs, or zero otherwise.

For credit bust, similar procedures are followed, but in the opposite direction. The credit bust occurs when $\tilde{C}_t \leq -1.65\sigma_{\tilde{C}_t}$ holds, and the value of negative one is taken when a credit bust happens. The formulas for credit boom and bust are presented in the equation (4.2).

Credit boom: $\tilde{C}_t > 1.65\sigma_{\tilde{C}_t}$

Credit bust: $\tilde{C}_t \leq -1.65\sigma_{\tilde{C}_t}$

(4.2)

The observations that are not identified as either credit booms or busts are characterized as normal or tranquil periods.

4.4.3 Credit Turning Point

To date the credit cycles, this study borrows the classical definition from the business cycle literature based on turning points in the level of aggregate economic activity (Burns and

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The value 1.65 is chosen because it falls in the 5 percent upper tail of the standard normal distribution.
Mitchell, 1947). To locate the turning point, this study adopts a turning points algorithm that is originally suggested by (Bry and Boschan, 1971). The process begins with decomposing the series into the trend and cyclical component. This approach generates credit cycles as deviations from the trend. The turning point algorithm then searches for credit peaks and troughs over the credit series.

The turning point algorithm program first finds turning points (peaks/troughs) in credit series $C_t$ at time $t$ and ensures that peaks and troughs alternate. Credit peaks occur at time $t$, and are described in equation (4.3), and troughs are defined in equation (4.4).

Credit peak:

$$C_{t-k} \ldots < C_{t-1} < C_t > C_{t+1} \ldots C_{t+k} \quad \text{(4.3)}$$

Credit trough:

$$C_{t-k} \ldots < C_{t-1} > C_t < C_{t+1} \ldots C_{t+k} \quad \text{(4.4)}$$

In the above equations, $k$ is called symmetric window parameter; it needs to be set by the user. Harding and Pagan (2002) suggest $k=5$ for monthly data. Once the turning points have been determined, the episodes of credit expansion (between trough and peak) or credit contraction (between peak and trough) can be identified. Figure 4.1 illustrates a credit trough and peak.
4.4.4 Cycle Co-movement

To measure the degree of co-movement among credit variables, this study uses the concordance statistic developed by Harding and Pagan (2002). This measure has been implemented at the IMF by (Cashin et al., 1999; McDermott and Scott, 2000). While Cashin et al. (1999) adopt this method to analyse the concordance for commodity good prices, McDermott and Scott (2000) use it to examine the concordance of business cycles in the OECD economies. This study adopted a concordance index to investigate co-movement among credit series, particularly between total credit and various credit subcomponents such as working capital, investment and consumption credit. The concordance index is computed as follows. Once the turning points (peaks/troughs) of a variable $y$ and $x$ have been identified (see equations 4.5 and 4.6), we define the binary variable $s_{y,t}$ and $s_{x,t}$ such that:
\[ s_{y,t} = \begin{cases} 1 & \text{if y is in expansion at t} \\ 0 & \text{otherwise} \end{cases} \] (4.5)

\[ s_{x,t} = \begin{cases} 1 & \text{if x is in expansion at t} \\ 0 & \text{otherwise} \end{cases} \] (4.6)

The credit expansion is the time from a trough to a peak, while contraction is from a peak to a trough. The concordance statistic refers to the number of periods (months) in which two variables (e.g. total credit and working capital credit) coincide at the same phase of the cycle. The concordance index between \( y \) and \( x \), \( concordance_{yx} \), is defined as the number of months where \( y \) and \( x \) are identified simultaneously in the same phase, as expressed in equation (4.7).

\[ Concordance_{yx} = \frac{1}{T} \sum_{t=1}^{T} [s_{y,t}s_{x,t} + (1 - s_{y,t})(1 - s_{x,t})] \] (4.7)

Thus, \( concordance_{yx} \), is equal to 1 if \( y \) and \( x \) are always in the same phase (perfect concordance), and 0 if \( y \) and \( x \) are always in the opposite phase (perfect disconcordance). A value of 0.5 indicates the lack of any systematic relationship in the dynamic of the variables (Avouyi-Dovi and Matheron, 2005)

### 4.4.5 Determinants of Credit Boom

This study examines determinants of credit cycles with specific concern given to the role of credit growth, new credit approval and residential housing prices in episodes of credit boom. The binomial logistic is adopted for model specification. The dependent variable \( y_t \) is a dummy variable, which takes the value of one when the economy enters a credit boom and
zero otherwise, excluding other credit boom years. The model specification is expressed in equation (4.8) below:

\[ y_t = \alpha X_t + \varepsilon_t \]  

(4.8)

where \( y_t \) is a dummy variable indicating credit boom (value=1; or 0 otherwise) in the month \( t \) (\( t=1,2,\ldots,T \)), \( X_t \) is the vector of input factors, \( \alpha \) is a vector of unknown parameters to be estimated, and \( \varepsilon_t \) is the error term. The error term is independent and identically distributed with mean zero and finite variance. The vector inputs are: 1) annual credit growth in terms of annual percentage changes; 2) the logarithmic form of new credit approval over total credit; and 3) policy rate in percentage terms.

A rapid credit growth is often considered the main cause of a credit boom. Elekdag and Wu (2011) argue that excessive credit growth may lead to a credit boom, which tends to end abruptly, typically in the form of a financial crisis. Excessive growth of credit in the private sector also continues to be a key challenge in many countries (Hilbers et al., 2005). A rapid pace of credit expansion is generally supported by improving economic prospects and stable macroeconomic environments on the supply side. However, foreign financial institutions entering these markets with the objective of rapidly gaining market share have often aided the rapid expansion of credit. Due to the importance of credit variables, this study uses annual credit growth and ratio of new credit approval (to total credit) to represent the credit situation and its growth trajectory in a country.

Many empirical studies stress the importance of the policy rate as an explanatory factor in relation to credit boom episodes. For instance, low interest rates make it cheaper to borrow money, and hence encourage individuals and firms to take out credit from banks and financial institutions in order to finance greater spending and investment. This loose
macroeconomic policy stance appears to have contributed to the build-up of credit booms (Elekdag and Wu, 2011). A lower interest rate will reduce the cost of funds and mortgage repayments; which leaves households with more disposable income. It is also common that asset prices tend to rise significantly due to speculation practices in times of low cost of borrowing, which makes it attractive for households to buy more assets; and this can cause excessive credit growth in the economy. An excess in global liquidity as reflected by low global interest rates has also contributed to the overexpansion of credit in many countries. This excess in global liquidity led to a surge in foreign capital inflows, specifically into domestic banking channels that eventually can trigger an overexpansion of credit in a country.

The final model specification is presented in equation (4.9) below:

\[ y_t = \alpha_0 + \sum_{i=1}^{3} \alpha_i x_{it} + \varepsilon_t \]  

(4.9)

where:

- \( x_{1t} \) is annual credit growth at time \( t \)
- \( x_{2t} \) is new credit approval to total credit at time \( t \)
- \( x_{3t} \) is policy rate (in percentage) at time \( t \)

Equation (4.9) is used to estimate the marginal effect of credit growth, new credit approval and policy rate on episodes of credit booms.
4.5 Data

The data set used in the study is collected from various sources including Banking Statistics of Bank Indonesia and the Indonesian Bureau of Statistics. The data span from January 2002 to May 2016, and all are in monthly frequency. A brief explanation of the data is presented below.

Credit growth. Credit growth is the annual percentage change in total credit. It is collected from the Banking Statistics of Bank Indonesia. All total credit series are in monthly frequency from January 2002 to June 2016, and are deflated by CPI to obtain real values. Total credit data refers to the lending relationship for a broad group of borrowers and lenders. The borrowers are non-financial corporations (both privately and publicly owned) and households, while the lenders include financial and non-financial corporations.

New credit approval ratio. New credit approval refers to the demand for credit in an economy, and a rising measure of new credit approval represents expanding credit activity in the economy. The new credit approval ratio is taken to represent the proportion of new credit relative to total credit. When the new credit approval ratio is very high, it is expected that there is a lot of credit creation, which may potentially lead to credit booms. The data on new credit approval is collected from the Banking Statistics of Bank Indonesia.

Policy rate. The data on policy rates is obtained from the Indonesian Bureau of Statistics and Banking Statistics of Bank Indonesia, and is based on Bank Indonesia Board of Governors meetings.
4.6 Empirical Results

4.6.1 Credit Gap

Across this study’s samples, there are 86 instances, or 49.7 percent of observations, which are positive credit gaps, while the remaining 87 instances (50.3 percent) are negative credit gaps. This implies that there are a relatively similar proportion of positive and negative credit gaps during the observation period. Within the credit subcomponents, it is expected that the credit gap would follow a relatively similar pattern to total credit. As expected, all types of credit subcomponents follow a relatively similar pattern to the total credit. Table 4.1 summarizes frequency of the credit gap.

<table>
<thead>
<tr>
<th>Type</th>
<th>Number of instances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive credit gap</td>
</tr>
<tr>
<td>Total credit</td>
<td>86 (49.7%)</td>
</tr>
<tr>
<td>Working capital</td>
<td>77 (44.5%)</td>
</tr>
<tr>
<td>Investment credit</td>
<td>77 (44.5%)</td>
</tr>
<tr>
<td>Consumption credit</td>
<td>87 (50.3%)</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

4.6.2 Credit Boom and Bust

There are a total of 173 episodes, of which 15 months are total credit booms (8.7 percent), 1 month is a credit bust (0.6 percent) and 157 months are normal periods (90.7 percent). The first credit boom occurred from January 2003 to January 2004, and the second credit boom took place from April to May 2008. The credit booms in the sample are mainly concentrated
in the year 2003; this credit boom could be attributed to very high credit growth prior to the year 2000. In the aftermath of the GFC, Indonesia’s average credit growth has been about 20 percent per annum, linked to loose monetary policy with low interest rate regimes following the crisis. Bank Indonesia maintained prolonged low policy rates as they viewed global recovery to be persistently hampered by weak demand, partly held down by unresolved crisis legacies. Since then, Bank Indonesia has continued to pursue loose monetary and macro-prudential policies with the aim of bolstering economic growth. A credit bust first occurred in February 2004, soon after the end of the first credit boom. Figure 4.2 illustrates the episodes of Indonesia’s credit booms (blue shaded areas) and busts (red shaded areas) for total credit and subcomponents of credit from January 2002 to May 2016.
It is also expected that the credit subcomponents would follow relatively similar patterns to total credit. The results, however, show differently. There are more instances of credit bust in consumption credit (7 instances), investment credit (7 instances), and working capital credit (4 instances) compared to credit busts in total credit, of which there is only one instance. Across samples, most months are characterised as normal or tranquil periods averaging 89.4 percent. Figure 4.3 summarizes our findings.
Following Mendoza and Terrones (2008), credit duration and magnitude are also computed. Credit duration refers to the number of months when one credit boom/bust episode takes place, while credit magnitude is defined as the deviation (from its trend) of credit at the peak level. The results show that the duration of credit booms are 13 months, while credit busts vary from 1 to 4 months. These results imply that credit booms last longer than credit busts. When credit booms take place, they sit longer, but are subsequently followed by credit busts that are short-lived. The results also confirm the findings of (Dell’Ariccia et al., 2016) that show credit booms tend to be larger and last longer than credit busts.

In regards to credit magnitude, Indonesia has experienced greater magnitudes during credit booms than credit busts. For example, at the peak of the credit boom, the magnitude reached 29 percent above the long-run trend. This large magnitude could be attributed to the
rapid development of the credit market in Indonesia and the country having a relatively low base credit level compared to developed economies. As distinct to the credit boom, the magnitude during credit busts is much smaller, at about 17 percent.

4.6.3 Credit Turning Point

According to the turning point algorithm, there are five credit peaks and three credit troughs in the total credit series. The first credit peak occurred in January 2004, followed by May and November 2008, December 2013, and May 2016. Conversely, credit troughs appeared in February 2004, June 2008, and January 2014. The first credit peak, in January 2004, could be attributed to rapid credit growth, especially in consumption credit. After the technology bubble in the year 2000, consumption credit in Indonesia recorded an unprecedingly a high growth rate averaging 47.2 percent per annum within the period 2000 to 2003, with working capital credit growth at 12.8 percent and investment credit at 13.1 percent.

More interestingly, around the time of the GFC, there are high incidences of credit peaks and troughs within a short-term horizon. There are two credit peaks (May and November 2008), and one credit trough (June 2008). One possible explanation for this is that there are high fluctuations and volatility across financial markets, including the credit market. Table 4.2 shows Indonesia’s credit peaks and troughs, while Figure 4.4 visualises the credit peaks and troughs from January 2002 to May 2016.
Table 4.2 Months of Credit Peaks and Troughs

<table>
<thead>
<tr>
<th>Credit peak</th>
<th>Credit trough</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan-04</td>
<td>Feb-04</td>
</tr>
<tr>
<td>May-08</td>
<td>Jun-08</td>
</tr>
<tr>
<td>Nov-08</td>
<td>Jan-14</td>
</tr>
<tr>
<td>Dec-13</td>
<td></td>
</tr>
<tr>
<td>May-16</td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

Figure 4.4 Indonesia’s Credit Peaks and Troughs from January 2002 to May 2016

Within the credit subcomponents, there are no large variations in terms of the number of months of credit peaks and troughs. A high degree of similarity could be explained by a high correlation in the cyclical components among credit variables ranging from 87 to 99 percent as presented in Table 4.3.
### Table 4.3 Credit Correlation

<table>
<thead>
<tr>
<th></th>
<th>Total credit</th>
<th>Working capital credit</th>
<th>Investment credit</th>
<th>Consumption credit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total credit</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Working capital credit</td>
<td>0.87</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment credit</td>
<td>0.87</td>
<td>0.98</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Consumption credit</td>
<td>0.89</td>
<td>0.99</td>
<td>0.98</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

### Table 4.4 Number of Credit Peaks and Troughs

<table>
<thead>
<tr>
<th></th>
<th>Credit peaks</th>
<th>Credit trough</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total credit</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Working capital credit</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Investment credit</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Consumption credit</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

Indonesia experienced three credit expansions and three credit contractions from January 2002 to May 2016. The credit expansions occurred from: February 2004 to May 2008 (51 months); June 2008 to December 2013 (65 months); and January 2014 to May 2016 (28 months). Conversely, the credit contractions happened from: January to February 2004 (1 month); May to June 2008 (2 months); and December 2013 to January 2014 (2 months). Overall, credit expansions are much longer than credit contractions. This confirms the previous finding of (Dell’Ariccia et al., 2016), that credit booms tend to last longer than credit busts.

In regards to the credit subcomponents, the credit expansions and contractions also follow similar patterns to total credit. Table 4.5 summarises our findings, while Figure 4.5 visualises the episodes of credit expansions and contractions from January 2002 to May 2016.
Table 4.5 Credit Expansions and Contractions

<table>
<thead>
<tr>
<th></th>
<th>Number of episodes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Credit expansion</td>
</tr>
<tr>
<td>Total credit</td>
<td>3</td>
</tr>
<tr>
<td>Working capital</td>
<td>3</td>
</tr>
<tr>
<td>Investment credit</td>
<td>3</td>
</tr>
<tr>
<td>Consumption credit</td>
<td>3</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

Figure 4.5 Total Credit Expansions and Contractions

Credit expansion, Credit contraction, total credit

4.6.4 Cycle Co-Movement

This study examines co-movement among total credit and credit subcomponents. The measure of concordance index developed by (Harding and Pagan, 2002) is used in the study.
Table 4.6 shows the concordance statistics among total credit, working capital credit, investment credit and consumption credit from January 2002 to June 2016. It is found that there are high concordances among credit variables. In other words, there are high proportions of credit variables that move together. Investment and consumption credits have a perfect concordance with each other, while investment, consumption and working capital credit has also a relatively high degree of concordance at about 92 percent with total credit. This high degree of concordance among variables could be explained by the increased interdependency between credit sectors in Indonesia. It also implies that credit sectors are likely to experience similar patterns of credit boom/bust episodes over the course of observations. Table 4.6 summarizes the concordance statistics.

<table>
<thead>
<tr>
<th></th>
<th>Total credit</th>
<th>Working capital credit</th>
<th>Investment credit</th>
<th>Consumption credit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total credit</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Working capital credit</td>
<td>0.92</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment credit</td>
<td>0.92</td>
<td>0.92</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Consumption credit</td>
<td>0.92</td>
<td>0.92</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

4.6.5 Determinants of Credit Booms

In this section, a probit regression model is used to examine determinants that could trigger credit booms. Table 4.7 shows that credit growth is significantly and positively associated with the credit booms. It can be interpreted that a one unit increase in credit growth raises the probability of a credit boom by 1.424, holding all other variables constant. The rapid credit
growth led to a credit boom, due to the fact that Indonesia needs robust credit growth for financial deepening. The financial deepening itself plays a critical role for Indonesia in that it supports strong economic growth.

An examination of the new credit approval ratio indicates that it is positive and statistically significant across all model specifications. It indicates that the creation of new credit positively increases the probability of credit booms. A one unit increase of new credit approval to total credit raises the probability of credit boom by 0.629. The policy rate is also statistically significant, suggesting the importance of the policy rate as a determinant for credit boom episodes in Indonesia. It has a negative sign, implying that a lower policy rate would increase demand for credit. A one-unit decrease of the policy rate increases the probability of a credit boom by 1.153. A policy rate cut will lower the cost of borrowing and thus drive asset prices up and increase the collateral value of the assets. As a result, there will be an increase in credit activities in the economy.

### Table 4.7 Baseline Model

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable: Dummy=1 when there is a credit boom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit growth</td>
<td>1.424***</td>
</tr>
<tr>
<td>(0.487)</td>
<td></td>
</tr>
<tr>
<td>New credit approval</td>
<td>0.629***</td>
</tr>
<tr>
<td>ratio</td>
<td>(1.325)</td>
</tr>
<tr>
<td>Policy rate</td>
<td>-1.153***</td>
</tr>
<tr>
<td>(0.417)</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>161</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

Notes: Coefficient estimates refer to marginal effect
*Significant at 10%, **significant at 5%, ***significant at 1%
Number in parentheses indicates standard errors
Several control variables that may have important contributions to credit booms are also included. The control variables are residential housing price index, inflation and GDP growth. Justiniano et al. (2015) show that a rapid increase in the housing price could lead to credit booms in the economy. Accordingly, this study adds a residential housing price index indicator into the equation. The data of the residential housing index is collected from the residential housing price survey of Bank Indonesia. The original data is in a quarterly series, which are converted into monthly frequency using cubic-spline interpolation technique.

Other potential drivers of credit booms are inflation and GDP growth, which are also included in the model specifications. The inflation and GDP growth data are in terms of annual percentage changes, and obtained from the Indonesia Bureau of Statistics and Banking Statistics of Bank Indonesia. The extended model is presented in equation (4.10).

\[
y_t = \alpha_0 + \sum_{i=1}^{3} \alpha_i x_{it} + \sum_{i=4}^{6} \beta_i x_{it} + \epsilon_t
\]  

(4.10)

where:

- $x_{1t}$ is annual credit growth at time t
- $x_{2t}$ is new credit approval to total credit at time t
- $x_{3t}$ is policy rate (in percentage) at time t
- $x_{4t}$ is residential housing price index at time t
- $x_{5t}$ is annual inflation (in percentage change) at time t
- $x_{6t}$ is annual GDP growth (in percentage change) at time t

Table 4.8 reports the results of the extended model with control variables. It is expected that a rapid increase in the housing price index could trigger a credit boom. Even though there is a positive coefficient on the housing price index, it is not statistically
significant (Model 1). The main reason for the insignificant impacts of the residential housing price on credit booms in Indonesia may be a persistent and continuous declining trend in property prices after the GFC. In fact, there are unprecedented housing price bubbles in the U.S and Eurozone countries, similar to Indonesia, before the GFC. Most of these bubbles are fuelled by excessive credit growth, specifically in the property credit sector.

Inflation plays a role in the determination of credit booms (Model 2). The results suggest that inflation is significant and decreases the possibility of credit booms. A one-unit decrease in inflation increases the probability of credit boom by 1.398. In times of low inflation, credit is more favourable due to the lower cost of funds; thus individuals and firms are keener to take on credit to finance greater spending and investment. With respect to GDP growth, which acts as a proxy for economic activities, during times of economic prosperity GDP growth tends to be strong and positive. However, this study finds no evidence that GDP growth has a significant contribution to credit booms (Model 3). This can be explained that the credit and business cycle (GDP) could have different characteristics and they do not coincide with each other. One can observe that credit growth is correlated with growth in the economy as a whole, but it does not mean that changes in the supply of credit are impacting the economic cycle. For instance, when economic growth is strong, borrowers may need less for financing due to high interest rate, and so credit growth slows. To some extent, this explanation may work in the other direction. When economic growth is slowing down, borrowers may also have less need for financing, thus credit growth will also slow.
Table 4.8 Extended Model

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit growth</td>
<td>1.538***</td>
<td>1.115**</td>
<td>1.445**</td>
<td>1.129**</td>
</tr>
<tr>
<td></td>
<td>(0.520)</td>
<td>(0.4875)</td>
<td>(0.509)</td>
<td>(0.470)</td>
</tr>
<tr>
<td>New credit approval</td>
<td>0.703***</td>
<td>0.537***</td>
<td>0.690*</td>
<td>0.464**</td>
</tr>
<tr>
<td>ratio</td>
<td>(1.464)</td>
<td>(1.346)</td>
<td>(0.194)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Policy rate</td>
<td>-1.419*</td>
<td>-0.222***</td>
<td>-0.793*</td>
<td>-0.207*</td>
</tr>
<tr>
<td></td>
<td>(0.857)</td>
<td>(0.761)</td>
<td>(0.911)</td>
<td>(0.143)</td>
</tr>
<tr>
<td>House price index</td>
<td>0.975</td>
<td>(0.736)</td>
<td></td>
<td>1.099</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.939)</td>
</tr>
<tr>
<td>Inflation</td>
<td>-1.398*</td>
<td></td>
<td>-0.136</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.844)</td>
<td></td>
<td></td>
<td>(0.887)</td>
</tr>
<tr>
<td>GDP growth</td>
<td></td>
<td></td>
<td>0.108</td>
<td>-0.292</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.245)</td>
<td>(0.281)</td>
</tr>
</tbody>
</table>

Number of observations: 161

Source: Author’s own calculation

Notes: Coefficient estimates refer to marginal effect
* Significant at 10%, ** significant at 5%, *** significant at 1%
Number in parentheses indicates standard errors

4.6.6 Determinants of the Magnitude of Credit Booms

To examine the determinants that potentially influence the magnitude of the credit boom, this study adopts an OLS regression. The dependent variable is the magnitude of the credit boom, and it is defined as the deviation of a credit series from its trend during the boom periods. The model specification is as presented in equation (4.11):

\[ y_t = \alpha_0 + \sum_{i=1}^{3} \alpha_i x_{it} + \sum_{i=4}^{6} \beta_i x_{it} + \epsilon_t \]  

(4.11)
Where $y_t$ is the magnitude of credit boom.

Table 4.9 reports the OLS regression results by explaining determinants that may influence the magnitude of credit booms. The results, in many cases, are comparable with previous findings. For example, increases in the credit growth and new credit approval ratio raise the probability of the credit boom. The policy rate is also statistically significant, suggesting the importance of the policy rate to determine the magnitude of credit booms in Indonesia. The results also show that the residential house price index, inflation and GDP growth are significant determinants across various model specifications in determining the magnitude of the credit boom. An increase in the residential house price and GDP growth increases the magnitude of the credit boom, while a rise in inflation decreases the magnitude of the credit boom. Overall, OLS regression results provide robust support to the previous findings.

Table 4.9 Magnitude of Credit Boom

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit growth</td>
<td>0.055*</td>
<td>0.834*</td>
<td>0.232*</td>
<td>0.222*</td>
<td>0.229*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>New credit approval ratio</td>
<td>0.127***</td>
<td>0.139*</td>
<td>0.153*</td>
<td>0.041*</td>
<td>0.027*</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.034)</td>
<td>(0.028)</td>
<td>(0.041)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Policy rate</td>
<td>-0.575***</td>
<td>-0.260***</td>
<td>-1.791***</td>
<td>-1.303***</td>
<td>-2.025***</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.303)</td>
<td>(0.209)</td>
<td>(0.9246)</td>
<td>(0.348)</td>
</tr>
<tr>
<td>House price index</td>
<td>0.025***</td>
<td>0.089***</td>
<td>-1.258***</td>
<td>-1.177***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.026)</td>
<td>(0.201)</td>
<td>(0.191)</td>
<td></td>
</tr>
<tr>
<td>Inflation</td>
<td></td>
<td></td>
<td>1.372***</td>
<td>2.720***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.437)</td>
<td>(0.495)</td>
<td></td>
</tr>
<tr>
<td>GDP growth</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

Notes: *Significant at 10%, **significant at 5%, ***significant at 1%
Number in parentheses indicates p-value
4.7 Conclusion

The objectives of this study are twofold: firstly, to present empirical evidence of the characteristics of the credit cycle in Indonesia; and secondly, to investigate the determinants of credit booms for a country. The findings suggest that Indonesia experiences more credit booms than credit busts. When credit booms take place, they last longer, and are followed by credit busts, which are short-lived and deeper. The results confirm the findings of (Dell’Ariccia et al., 2016), which find that credit booms tend to be larger and last longer than credit busts. The results demonstrate a significant and positive relationship between two variables, those being credit growth and new credit approval, to the occurrence of credit booms in Indonesia. A rapid credit growth and higher ratio of new credit approval contributes not only to an increase probability of the credit booms, but also to the higher magnitude of the credit booms. The results also find that a lower policy rate increases the probability of the credit booms. In relation to the magnitude of a credit boom, the findings suggest that an increase in residential house price index and GDP growth will increase the magnitude of the credit boom, while a rise in inflation decreases the magnitude of the credit boom.
5.1 Introduction

Following the 1997 Asian Financial Crisis, Indonesia, as Southeast Asia’s largest economy, has had an uphill struggle to rebuild itself through the use of stringent financial and fiscal policies. Consequently, this has prompted the Indonesian government to institute legislation, Law No. 17/2003, firmly advocating for the country’s debt not to exceed 60 percent of GDP. Indonesia has maintained a favourable debt and fiscal position in comparison to its regional neighbours with a debt-to-GDP ratio that has consistently declined from 87.4 percent in 2000 to about 27 percent in 2016. This debt-to-GDP ratio is relatively low, and below the legal maximum debt-to-GDP ratio. Many developed and developing countries, however, have debt-to-GDP ratios that are much higher than Indonesia’s.

On local debt, Indonesia’s subnational debt has gradually decreased following the decentralisation process that started in 2001 (Petersen and Tirtosuharto, 2012). The decentralisation reduced local government borrowing as the central government imposed stricter regulations on local governments, which limited their ability to take out foreign loans. Furthermore, local borrowing is subdued due to the limited tenure of heads of local government, which creates a myopic view in the planning and budgeting process that prioritises smaller short-term investments.

In Indonesia, levels of economic growth vary across regions. For example, Java and Bali have enjoyed higher economic growth due to large infrastructure projects, while other
areas have lacked these developments. There is also considerable income-per-capita disparity across the regions. East Kalimantan, Riau and DKI Jakarta continue to be some of the richest provinces, whilst East and West Nusa Tenggara have always been among the poorest. Resosudarmo and Vidyattama (2006) identify some determinants of this regional disparity such as levels of natural endowment, human capital and educational attainment. Further, Mahi (2014) investigates the competitiveness across regions and found that different levels of competitiveness also resulted in regional income level disparity. The results also suggest regions such as DKI Jakarta, Java, Bali, Riau and East Kalimantan are the most competitive and industrious regions in the country. The results further show that Java is the most competitive region, while provinces in eastern Indonesia are the least competitive in the country.

Until recently, examination of the impact of local debt on regional growth has been more or less absent from the literature. Wu (2014) analyses the relationship between local government debt and regional growth in China and finds that there is an inverted U-shaped relationship between local debt and regional growth. For Indonesia, even though the role of local debt in determining national growth is relatively insignificant since local borrowing as a percentage of GDP is less than one percent (Lewis, 2003), there are no prior studies analysing the impact of local debt on regional growth. Despite low levels of local debt in Indonesia, the role of local debt in affecting regional growth remains significant as many infrastructure projects completed at the local level are funded through these debt instruments.

This study goes on to extend the work of Wu (2014) by presenting an empirical analysis of the relationship between long-term local debt and regional growth in Indonesia. The significance of the study lies primarily in its importance in understanding the optimal level of local government debt. In regard to the local debt level, this study supplements previous studies on the topic, as well as economic theories that may be employed to explain
the relationship between local debt and regional growth. Econometric techniques will also be used to determine optimal local debt levels for higher regional growth.

The remainder of the chapter will proceed as follows. Section 5.2 presents a review of the literature. Section 5.3 covers the method and Section 5.4 is the description of data. Section 5.5 provides an analysis of results, while Section 5.6 concludes.

5.2 Review of Literature

Many empirical studies have been conducted to examine the relationship between debt and economic growth. For example, Georgiev (2012) examines the relationship between debt and economic growth in 17 European countries and found a positive and negative relationship between debt and economic growth, while Kasidi and Said (2013) suggest only a positive relationship exists between debt and economic growth. Debt instruments have long been used in many countries to finance infrastructure projects, which have been considered as positive catalysts in boosting economic growth.

A number of methods have been employed to explain the relationship between debt and economic growth. One such tool is turning point analysis, also known as the threshold method, which examines the point at which the debt level begins to detrimentally impact long-term economic growth. The turning point approach is a reliable method that may be used to evaluate the relationship between debt levels and economic growth. This method is able to identify which debt level is optimal for economic growth.

On the subject of debt and economic growth analysis, there are mixed results regarding the optimal level of debt that would maximise economic growth. In more recent studies, some evidence is shown to suggest the existence of a non-linear relationship between
debt and economic growth - that is, debt will have a positive impact on economic growth up to a certain level, but beyond that level it will have an adverse effect on growth. Pattillo et al. (2002) find that the impact of debt on economic growth is negative when the debt level exceeds a threshold of 35-40 percent of GDP based on panel studies of 93 emerging countries from 1969 to 1998, while Rogoff and Reinhart (2010) study of selected OECD countries suggest that the debt threshold to be at 90 percent of GDP. Simply put, debt remains growth enhancing up to its threshold of 90 percent of GDP, but beyond this point debt becomes counterproductive to economic growth. More recently, Checherita-Westphal and Rother (2012) also suggest a high debt-to-GDP ratio of more than 90 percent would have a detrimental impact on economic growth.

The Granger causality test has also been used to examine the relationship between debt and economic growth. For example, Al-Zeaud and Al-Awawdeh (2014) examine the relationship between debt and GDP for Jordan. They used this approach in the determination of whether the debt Granger caused GDP growth or vice versa. Other statistical tests such as the Augmented Dickey-Fuller test, or the co-integration test, could also be employed. The co-integration test is helpful in examining whether there is a long-term equilibrium relationship between variables - in particular, between debt and economic growth.

There are several channels through which debt can affect economic growth. A study conducted by (Checherita-Westphal and Rother, 2012) on the 12 Euro-area countries from 1970 to 2000 examine the different avenues through which debt affects the rate of economic growth. These include total factor productivity, private savings, public investment and real interest rates. It is found that large budget deficits would push interest rates up, crowd-out private investment and hamper economic growth. Schclarek (2004) finds that capital accumulation is the main channel through which debt affects growth, and Pattillo et al. (2002) argue capital accumulation and total factor productivity are the most important channels.
Multiple economic theories have been used to explain the relationship between debt and economic growth. The debt overhang hypothesis (Krugman, 1988) argues that economic growth of a country may progressively slow down when a country has high debt. Large debt would limit a country’s capacity to seek foreign funds to finance productive activities in the economy, resulting in slower economic growth. As the magnitude of debt increases, uncertainty about how the government can fulfil its debt servicing obligations may also increase. There may be an expectation that the debt service would be financed by distortionary measures such as raising taxes (Agénor and Montiel, 2008). In Pakistan, Imran et al. (2016) present evidence of this debt overhang hypothesis and find that high debt levels actually have an adverse impact on economic growth.

The debt Laffer curve provides a sound explanation for the debt overhang hypothesis. This theory is first introduced by Jeffrey Sach and later formalised by Paul Krugman (Trandafir and Brezeanu, 2011). The debt Laffer curve illustrates an economic phenomenon whereby a country which accrues too much debt will experience efficiency losses, as a large proportion of debt will be used for servicing debt obligations, not for productive uses (Greiner and Flaschel, 2010). The debt Laffer curve suggests that debt only has a positive impact on economic growth up to a certain threshold level, but beyond this level its impact would be counterproductive. Osinubi et al. (2010) argue that high accumulation of debt beyond the threshold limit would slow economic growth, an argument well illustrated by the debt Laffer curve. In addition, as debt increases, expected debt repayments also begin to fall (Cohen, 1993).

The debt threshold value may be determined exogenously through the use of a methodical or judgemental approach. This threshold can be regarded, as the optimal level of debt, beyond which there will be debt overhang. The threshold value can be estimated by scattering GDP growth against debt using a quadratic curve. Figure 5.1 shows that the area to
the right of the curve indicates accumulation of debt stocks, where increased debt stocks would act as taxes on investments. Having a large debt accumulation would decrease the probability of debt repayments, thus the threshold is the point at which debt is optimal for economic growth.

![Debt Laffer Curve](image)

**Figure 5.1 Debt Laffer Curve**

Further, Megersa (2015) provides evidence from his study conducted in the Sub-Saharan African countries on how the Laffer curve could be used to explain the relationship between debt and economic growth. He finds that there is an inverted U-shaped relationship between debt and economic growth and his findings also support the debt overhang hypothesis - which debt positively contributes to a country's economic growth only up to a certain degree. His results confirm the findings of (Pattillo et al., 2002) that study 93 developing countries from 1972 to 1998 which also suggest an inverted U-shaped relationship between debt and economic growth.

Endogenous growth theory has been also used to explain the relationship between debt and economic growth. Kobayashi (2013) suggests that economic growth is primarily the result of endogenous factors, not external forces such as external debt. This theory holds that
endogenous factors such as investment in human capital, innovation and knowledge are significant contributors to economic growth, and, thus, having debt would be counterproductive and might reduce economic growth. Greiner and Flaschel (2010) adopt this endogenous growth theory to examine the relationship between debt, budget deficits and GDP growth. The results suggest that an increase in the budget deficit and higher debt would result in a decline in economic growth.

At the local level, however, there are few studies examining the impact of local debt on regional growth. In Indonesia, Petersen and Tirtosuharto (2012) argue that local government debt levels are not significant enough to warrant further investigation due to the strict regulations imposed by the central government on local government borrowing. Similar arrangements also exist in many other parts of the world. With the Global Financial Crisis in 2008/2009 and Asian Financial Crisis in 1997, the focus of many analyses has shifted from the regional to the national level (Georgiev, 2012). As such, very little data of decent quality exists to support research that examines the relationship between local debt and regional growth. Further, Wu (2014) suggests that limited data quality and data availability at the local level may hinder a thorough analysis of the relationship between local debt and regional growth.

5.3 Method

This study investigates the relationship between the local government debt-to-Gross Regional Product (GRP) ratio and per-capita GRP growth rate in a sample of 33 provinces in Indonesia. The data are primarily collected from Indonesia’s Bureau Statistical Office database, covering the period from 2008 to 2013 (198 observations). The empirical growth model is generally based on an equation relating the real GRP-per-capita growth rate to the
initial level of income per capita, local debt-to-GRP ratio, investment, human capital, population growth, fiscal capacity ratio and CPI. This model is augmented to include the level of local government debt as a share of GRP. The dependent variable is the growth rate of GRP per capita ($GRPG$) and the explanatory variables are the initial level of GRP ($Y$) per capita at a constant price level (2000 prices), local government debt-to-GRP ($D$) and its squared term of debt-to-GRP ($D^2$). A natural logarithm of 5-year lagged GDP per capita income is used as the initial per-capita income (See Table 5.1).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$GRPG_{it}$</td>
<td>GRP per capita growth rate in year $t$</td>
</tr>
<tr>
<td>$\ln(Y_{i,t-5})$</td>
<td>Natural logarithm of 5-year lagged GRP per capita income in year $t$</td>
</tr>
<tr>
<td>$D_{it}$</td>
<td>Local government debt to GRP in year $t$</td>
</tr>
<tr>
<td>$D_{it}^2$</td>
<td>A squared term local government debt to GRP in year $t$</td>
</tr>
<tr>
<td>$POPG_t$</td>
<td>Population growth in year $t$</td>
</tr>
<tr>
<td>$HDI_t$</td>
<td>Human Development Index in year $t$</td>
</tr>
<tr>
<td>$INVGRP_t$</td>
<td>Investment to GRP in year $t$</td>
</tr>
<tr>
<td>$FISCI_t$</td>
<td>Fiscal Capacity Ratio in year $t$</td>
</tr>
<tr>
<td>$CPI_t$</td>
<td>Consumer Price Index in year $t$</td>
</tr>
</tbody>
</table>

The augmented growth model is given in equation (5.1).

$$GRPG_{it} = \alpha + \beta \ln(Y_{i,t-k}) + \gamma D_{it} + \varnothing (D_{it})^2 + \Sigma \delta_j X_{ijt} + \mu_i + \nu_t + \varepsilon_{it} \quad (5.1)$$

Where $GRPG_{it}$ represents the regional growth rate of GRP per capita in region $i$ at time $t$, and $Y_{i,t-k}$ represents initial income per capita in region $i$ in period $t$ with the lagged term $k$. The study uses a five-year lag of initial income level as suggested by (Barro, 1991; Sala-I-Martin, 1997; Wu, 2014). Since this study focuses on the examination of a nonlinear impact of local debt on growth, a quadratic form of debt variable $D_{it}^2$ is used in the equation. $X$ is a set of control variables that may affect regional economic growth; $\mu_i$ represents the province fixed
effects; \( v_t \) is the time fixed effects; and \( \epsilon_{it} \) is the error term. The error term is independent and identically distributed with a mean of zero and finite variance.

There are five control variables in this study. The first control variable is population growth (\( POPG \)), to capture the effect of population in the region on local economic growth. A higher population growth creates higher aggregate demand in the region; therefore, it is expected to have a positive effect on local growth. The second variable is the Human Development Index (\( HDI \)), which is a composite statistic of life expectancy, education and income indices used to rank countries or regions. Data on HDI by region is widely available in Indonesia and higher values of HDI represent better quality of life and educational capabilities, therefore it is also expected to have positive effect on the local growth. The third control variable is total investment, as comprised by domestic and foreign investment as a proportion of GRP (\( INVGRP \)). A higher value of investment ratio would have a positive impact on infrastructure development and on local growth, thus it is expected to have a positive coefficient. The fourth control variable is the fiscal capacity ratio (\( FISCI \)), which is a measure that can be used to assess the health of local finances when seeking domestic and foreign funds. The FISCI indicator classifies regions into three categories: high, medium and low fiscal capacity. Regions with a high fiscal capacity have a better ability to borrow and repay loans. The FISCI is calculated as follows:

\[
\text{Fiscal capacity ratio (FISCI)} = \frac{(PAD+DBH+DAU+LP)-BP}{\sum \text{Poor people}}
\]  

(5.2)
where PAD is actual local government revenue; DBH is local revenue from tax and non-tax shares; DAU is general allocation; LP is specific allocation; and BP is personnel expense.

The fifth control variable is the consumer price index (CPI), which captures the movement of price levels at the local level. 2007 is used as the base year. Given the relatively small dimensions of the local government cross-sections and the need to control for regional specific characteristics, the equation also considers regional fixed effects.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRP Growth (GRPG)</td>
<td>0.055</td>
<td>0.043</td>
<td>-0.07</td>
<td>0.280</td>
</tr>
<tr>
<td>LNGRP (lnY)</td>
<td>15.830</td>
<td>0.670</td>
<td>14.390</td>
<td>17.680</td>
</tr>
<tr>
<td>Local debt-to-GRP (D)</td>
<td>0.156</td>
<td>0.146</td>
<td>0.00</td>
<td>0.859</td>
</tr>
<tr>
<td>Population Growth (POPG)</td>
<td>0.019</td>
<td>0.009</td>
<td>0.00</td>
<td>0.054</td>
</tr>
<tr>
<td>Human Development Index (HDI)</td>
<td>0.721</td>
<td>0.030</td>
<td>0.640</td>
<td>0.786</td>
</tr>
<tr>
<td>Investment/GRP (INVGRP)</td>
<td>0.058</td>
<td>0.08</td>
<td>0.00</td>
<td>0.532</td>
</tr>
<tr>
<td>Fiscal capacity ratio (FISCI)</td>
<td>0.082</td>
<td>0.121</td>
<td>0.00</td>
<td>0.743</td>
</tr>
<tr>
<td>Consumer Price Index (CPI)</td>
<td>1.272</td>
<td>0.12</td>
<td>1.077</td>
<td>1.580</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

5.4 Data

In Indonesia, local governments are allowed to take out long-term loans for capital development, subject to several conditions. One condition is that local government borrowing should be used to finance infrastructure that directly generates subnational own source revenue. Another criterion is that the outstanding debt of a subnational government may not exceed 75 percent of the previous year’s general revenues (defined as all revenues except special purpose grants and emergency grants) and the debt-service coverage ratio must be at least 2.5. Furthermore, local governments cannot borrow more than the maximum amount
determined by the central government, nor can they borrow while past loans remain in arrears. These strict regulations have limited borrowing by local governments and Regional Water Authorities (Perusahaan Daerah Air Minum/PDAMs), thus limiting public capital spending at the local level.

The vast majority of local debt has been primarily channelled through two central government mechanisms: Subsidiary Loan Agreement (SLA) and Regional Development Account (RDA). There has only been a very small amount of regional borrowings from other financial institutions, such as regional developments or state or commercial banks, and most of these loans have been used to assist in the management of cash flow. SLA is the on-lending mechanism for major donor funds and it has been closely associated with the Integrated Urban Infrastructure Development Programs (IUIDP) of the World Bank and the Asian Development Bank. RDA is the Indonesian government’s channel for lending state budget funds to local governments and local government enterprises (BUMDs). The account has been used to finance regional infrastructure. The SLA and RDA loan mechanisms are both managed by the Ministry of Finance. A large portion of local debt is from BUMDs and PDAMs, especially those located in urban areas. These two mechanisms, in general, make up about two-thirds of total borrowing (Lewis, 2003). In recent years, Indonesia’s local governments have not borrowed much to finance their capital spending (Lewis, 2007). It is estimated that Indonesia’s local debt between 1975 and 2004 is less than one percent of GDP. This low level of local borrowing has a negative consequence for investment in infrastructure, particularly the delivery of water services at the local level.

Most BUMDs provide public sector goods such as water services, electricity and transportation while finance/rural banking is the dominant sector in terms of assets. In 2013, total assets of finance-related BUMDs accounted for about 92 percent of total BUMDs assets, while water services only comprised about 4.4 percent of total assets (see Table 5.3). Short-
term debt accounted for 77 percent of BUMDs’ debt, while the remaining 23 percent is long-
term debt. Having a large portion of short-term local debt poses risks for the management of local debt solvability including debt arrears, Lewis (2007) estimates that Indonesia’s local debt arrears rate is surprisingly high, at about 50% in 2004. About one-third of the total is arrears on principal, while the remainder comprised arrears on interest, service charges and penalties. The arrears on penalties alone make up nearly 30% of the total. Penalties, charged by the central government for late payment or non-payment, have been an item of significant contention between the central and local governments over the years.

In Indonesia, BUMDs are governed under the Ministry of Home Affairs, while state owned enterprises (BUMNs) are under the administration of the Ministry of State Owned Enterprises. The ownership of BUMDs can be classified into two major categories: provincial-owned and district/city-owned. In 2013, there are 100 provincial-owned BUMDs and 658 district/city-owned BUMDs. The number of district/city-owned BUMDs is much higher because most infrastructure projects are implemented at the city/district level.
Table 5.3 BUMDs Asset, Equity, and Net Profit According to Type of Business Operation for the Year 2013 (in Billion Rupiah)

<table>
<thead>
<tr>
<th>Category</th>
<th>Total Assets</th>
<th>Total Equity</th>
<th>Net Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, Forestry and Fishing</td>
<td>712</td>
<td>454</td>
<td>33</td>
</tr>
<tr>
<td>Mining and Quarrying</td>
<td>2122</td>
<td>1395</td>
<td>520</td>
</tr>
<tr>
<td>Processed industry</td>
<td>931</td>
<td>684</td>
<td>10</td>
</tr>
<tr>
<td>Electricity and Gas</td>
<td>453</td>
<td>329</td>
<td>5</td>
</tr>
<tr>
<td>Water service, recycling and rubbish service</td>
<td>19,574</td>
<td>11,247</td>
<td>684</td>
</tr>
<tr>
<td>Construction</td>
<td>922</td>
<td>640</td>
<td>9</td>
</tr>
<tr>
<td>Wholesale, retail and vehicle maintenance</td>
<td>617</td>
<td>508</td>
<td>22</td>
</tr>
<tr>
<td>Transportation and warehouse</td>
<td>483</td>
<td>379</td>
<td>13</td>
</tr>
<tr>
<td>Accommodation and catering service</td>
<td>817</td>
<td>707</td>
<td>19</td>
</tr>
<tr>
<td>Finance and insurance</td>
<td>405,586</td>
<td>54,766</td>
<td>11,522</td>
</tr>
<tr>
<td>Real estate</td>
<td>8607</td>
<td>4019</td>
<td>261</td>
</tr>
<tr>
<td>Professional service and consultancy</td>
<td>58</td>
<td>54</td>
<td>0.1</td>
</tr>
<tr>
<td>Rental service and travel agent</td>
<td>130</td>
<td>86</td>
<td>19</td>
</tr>
<tr>
<td>Medical and social service</td>
<td>141</td>
<td>130</td>
<td>41</td>
</tr>
<tr>
<td>Art and recreation</td>
<td>92</td>
<td>88</td>
<td>9</td>
</tr>
</tbody>
</table>

Source: BUMNs and BUMDs Financial Statistics 2013, Indonesia’s Statistical Bureau Office

BUMD debt-to-GRP\(^6\) is used to indicate local governments’ ability to repay debt obligations. Figure 5.2 shows that some regions have a considerably high ratio of local debt-to-GRP, and that this specifically occurs in underdeveloped areas such as Maluku and Papua.

\(^6\)The Gross Regional Product (GRP) is based on 2000 constant market price.
This study uses BUMD debt as a proxy for Indonesia’s local debts. Lewis (2003) suggests that BUMD debt comprises about two thirds of local debt in Indonesia, thus using BUMD debt could be a good measure to represent the total local debt.
5.5 Estimation Results

First, this study presents a stylised fact that a higher level of local government debt would have a negative effect on local growth. This observation is based on the averages of local growth and local debt-to-GRP for 33 provinces in Indonesia from 2008 to 2013 (Figure 5.3). The average values of both data series are taken to minimise data fluctuations over the period.

The results show that a one-percentage point increase in the debt-to-GRP ratio would result in a 0.075 percentage point decrease in local growth. The $t$-test also shows that the debt-to-GRP ratio variable is significant at the 5 percent significance level. The existence of a negative linear relationship between local debt and regional growth may be explained by the fact that higher levels of debt generally hinder local growth.

\[
\text{GRP growth} = 0.075 - 0.075 \times \text{DEBTGRP}
\]

Figure 5.3 Local Debt-to-GDP Ratio and Regional Growth
5.5.1 Linearity Test

An ordinary least squares (OLS) regression is applied to investigate the linear impact of the local debt-to-GRP variable on regional growth. First, the linear form of the local government debt-to-GRP ratio, initial income per capita and control variables are used in the model. A five-year lagged term of the income variable is used in the study as suggested by (Checherita-Westphal and Rother, 2012; Wu, 2014). The control variables used in the study include the population growth rate which reflects the size of population and workforce, human development index (HDI) as a proxy variable for human capital, investment-to-GRP ratio which represents infrastructure development, fiscal capacity ratio \((FISCI)\) which reflects the health of local finances and CPI to capture the impact of price level dynamics at the local level. The following linear regression specification is used in the study.

\[
GRPG_{it} = \alpha + \beta_1 \ln(Y_{i,t-5}) + \gamma D_{it} + \beta_4 POPG_{it} + \beta_2 HDI_{it} + \beta_3 NVGRP_{it} + \\
\beta_4 FISCI_{it} + \beta_5 CPI_{it} + \varepsilon_{it} \tag{5.3}
\]

The correlation matrix, when calculated, allows the examination of relationships among explanatory variables. There are seven variables: a lagged initial income, debt and five control variables, thus there are 49-paired correlations in total (see Table 5.4). The correlation is considerably higher between income per capita and fiscal capacity ratio (68 percent), income per capita and HDI (58 percent) and HDI and FISCI (50 percent). As this study focuses on local debt-to-GRP (DEBTGRP) as the main variable of interest, the correlation coefficients between DEBTGRP and other explanatory variables are relatively low, reducing the risk of multicollinearity.
Table 5.4 Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>LNGRP</th>
<th>DEBTGRP</th>
<th>POPG</th>
<th>HDI</th>
<th>INVGRP</th>
<th>FISCI</th>
<th>CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>InY</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>-0.09</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POPG</td>
<td>0.20</td>
<td>0.03</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HDI</td>
<td>0.58</td>
<td>-0.13</td>
<td>-0.14</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INVGRP</td>
<td>-0.01</td>
<td>-0.03</td>
<td>-0.07</td>
<td>0.15</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FISCI</td>
<td>0.68</td>
<td>-0.12</td>
<td>0.12</td>
<td>0.50</td>
<td>0.13</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>0.09</td>
<td>0.20</td>
<td>-0.11</td>
<td>0.15</td>
<td>0.25</td>
<td>0.17</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Author’s own estimates

5.5.2 Nonlinearity Test

To evaluate the nonlinear relationship between local debt and regional growth in Indonesia, a panel growth regression model augmented with a squared term of the debt variable is used in the study. Some potential explanatory variables to assess the impact on local growth are considered. The model specification with a squared debt term is presented as equation (5.4).

\[
GRPG_{it} = \alpha + \beta_1 \ln(Y_{it-5}) + \gamma D_{it} + \varphi(D_{it})^2 + \beta_1 POPG_{it} + \beta_2 HDI_{it} + \beta_3 INVGRP_{it} + \\
\beta_4 FISCI_{it} + \beta_5 CPI_{it} + \varepsilon_{it} \tag{5.4}
\]

The OLS results are presented in Table 5.5. Without control variables, the expected negative coefficients of the debt variable and a squared debt variable are both significant at a level of 1 and 5 percent respectively. It could be inferred that a negative sign of the squared debt term reflects the concavity or the inverted U-shaped relationship between local
government debt-to-GRP ratio and per-capita GRP growth. The coefficient of initial income level is negative but not significant. With the control variables, the results also show that the debt and squared debt variables are both significant at the 1 percent level. Of the control variables, only investment-to-GRP and fiscal capacity ratios are significant, while the remaining control variables are not significant. The results across all OLS models show a highly statistically significant nonlinear relationship between the local government debt-to-GRP ratio and per-capita GRP growth for the 33 provinces in Indonesia.
### Table 5.5 Estimation Results

<table>
<thead>
<tr>
<th></th>
<th>OLS Pooled Regression</th>
<th>Fixed Effect</th>
<th>Random Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>( D )</td>
<td>-0.065***</td>
<td>-1.380***</td>
<td>-0.070*</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.00)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( D^2 )</td>
<td>-1.310**</td>
<td>-1.60***</td>
<td>-0.120</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.001)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>( \ln Y ) LAG(-5)</td>
<td>-0.006*</td>
<td>-0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.00)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>POPG</td>
<td>0.430</td>
<td>0.270</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.370)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>HDI</td>
<td>-0.001</td>
<td>0.005</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.800)</td>
<td>(0.570)</td>
<td>(0.390)</td>
</tr>
<tr>
<td>INVGRP</td>
<td>0.050</td>
<td>0.060**</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.030)</td>
<td>(0.630)</td>
</tr>
<tr>
<td>FISCI</td>
<td>-0.030</td>
<td>-0.053**</td>
<td>0.0130</td>
</tr>
<tr>
<td></td>
<td>(0.220)</td>
<td>(0.080)</td>
<td>(0.830)</td>
</tr>
<tr>
<td>CPI</td>
<td>0.001</td>
<td>0.001</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.210)</td>
<td>(0.290)</td>
<td>(0.440)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.170***</td>
<td>0.150</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.270)</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>0.070</td>
<td>0.080</td>
<td>0.080</td>
</tr>
<tr>
<td>Hausman test</td>
<td>5.510*</td>
<td>7.150*</td>
<td>24.850***</td>
</tr>
</tbody>
</table>

Source: Author’s own calculation

Notes: *Significant at 10%, **significant at 5%, ***significant at 1%. Number in parentheses indicates p-value.
5.5.3 Debt Threshold

The results suggest the existence of a nonlinear relationship between local debt and regional growth in Indonesia. The debt threshold is calculated to examine the level at which local debt becomes counterproductive to regional growth. The computation involves two processes. The first step is to take the first derivative of the equation with respect to the debt-to-GRP ratio (see equation 5.5). The second step is to ensure that the turning point is a maximum (Kumara and Cooray, 2013).

\[
\frac{\partial \text{GRP}_{it}}{\partial D_{it}} = \gamma + 2\phi(D_{it}) = 0 \tag{5.5}
\]

The first order derivative is the turning point of local debt-to-GRP, while the second order derivative ensures that there is a maximum at that turning point. From the results, it is estimated that the turning point of local debt-to-GRP in Indonesia is between 55 and 75 percent. It implies that local government debt-to-GRP above these thresholds would have a negative impact on regional growth. These thresholds are far higher than the estimated threshold value for China, which is about 35 percent of GRP (Wu, 2014).

5.5.4 Panel Data Estimation

The full panel model specification used in the study is presented as in equation (5.6):
\[ GRPG_{it} = \alpha + \beta_1 \ln(Y_{i,t-5}) + \gamma D_{it} + \phi(D_{it})^2 + \beta_1 POPG_{it} + \beta_2 HDI_{it} + \beta_3 INVGRP_{it} + \beta_4 FISCL_{it} + \beta_5 CPI_{it} + \mu_i + v_t + \varepsilon_{it} \]  

(5.6)

Where:

- \( \mu_i \) is a regional effect
- \( v_t \) is a time effect
- \( \varepsilon_{it} \) is an error term.

The Hausman test is used to determine the preferred panel model between fixed effects (FE) and random effects (RE). This test shows that the coefficients estimated by the FE and RE models are not the same. Both in a linear and nonlinear model, the FE model is preferred over the RE model, as the \( p \)-value resulting from the Hausman test is significant.

In the FE model, with or without control variables, the coefficient of the lagged term of initial income level is significant. Population growth has a positive coefficient and is significant at the 5 percent level (Model 7 and 8, Table 5.5), thus it is assumed that population growth positively influences local growth. The investment-to-GRP ratio has a positive coefficient (Models 3 and 4), indicating a positive relationship between investment and economic growth. The fiscal capacity ratio is also significant at the 10 percent level (Model 4), indicating that fiscally sound local governments tend to experience higher regional growth. The estimated coefficients of the debt term and squared debt term are both negative, but not significant. The estimated threshold debt level ranges from 45 to 53 percent.

The results indicate that OLS estimation provides evidence for a statistically significant nonlinear relationship between local government debt and regional growth. The coefficient of the quadratic local debt-to-GRP variable is negative, indicating an inverted
U-shaped relationship between local debt and regional growth. These results confirm the theoretical assumption that the impact of debt on growth is positive at low levels of debt, but beyond a certain level or threshold, a negative effect of debt on growth prevails.

5.5.5 Endogeneity

In the study of the causal relationship between local debt and regional growth, it is assumed that lower regional growth is the direct result of high local debt (Tica et al., 2014). Increased expenditure from debt would result in debt overhang and a crowding-out effect, resulting in slower economic growth, but causality can go in either direction. This is a significant endogeneity issue.

To mitigate these endogeneity issues, some researchers adopted the generalised method of moments (GMM), while others used the instrumental variables (IV) technique. Kumar and Woo (2010) advocate the use of GMM and suggest using initial starting levels of the dependent variable as an independent variable to address feedback effects. Further, Tica et al. (2014) conclude that GMM estimation can be used to curb inter-temporal endogeneity. Their findings suggest that the inter-temporal causal relationship may go in either direction, thus implying that the feedback effect would significantly regress regional growth as they do the same for local debt. Checherita-Westphal and Rother (2012) use the IV method to address endogeneity problem between two variables.

This study uses the GMM and IV approach to control the endogeneity problem. The estimators used are the GMM estimator and the two stage least square (2SLS) IV. The GMM estimator could correct for the possible heteroscedasticity and autocorrelation in the error structure by using a consistent estimator. The GMM matrix also provides some efficiency gains over the 2SLS estimator derived from the use of an optimal weighting
matrix, the over-identifying restrictions in the model and the relaxation of the independent and identical distribution assumption (Baum et al., 2015). The 2SLS IV estimator is also powerful and the advantages of using this approach are numerous. It does not require any distributional assumptions for the independent variables, it is computationally simple as it does not require the use of numerical optimisation algorithms, and it easily caters for nonlinear and interaction effects (Bollen and Paxton, 1998).

Endogeneity could arise from the debt variable itself. It is expected that reverse causation exists between local debt and regional growth. The estimations are continued once the endogeneity problem is first addressed. In the IV approach, the instrumental variables used are a lagged debt-to-GRP variable and the average of the debt level of the other regions. The debt-to-GRP variable is instrumented with the one-year lagged debt-to-GRP term and correlation between the debt variable \((D)\) and the one-year lagged term of the debt variable is considerably high, at around 94.25 percent.

While using lagged terms such as IV is relatively common in economic data analysis, it is problematic to use this measure considering the high persistence of the debt level variable. Thus, the average debt-to-GRP ratio of other regions is used for the instrumental variable. This instrumental variable has the advantage of not being directly related to the GRP growth when there is no spill over effect between local debt in one region and GRP growth in other regions. The correlation between debt variable \((D)\) with the mean neighbouring debt variable \((D)\) IV is relatively low at about 22 percent. One of the reasons for this low correlation is the wide disparity of regional growth and local debt patterns across regions in Indonesia. As the one-year lagged term debt variable \((D)\) has a higher correlation with the debt variable \((D)\) compared to debt variable \((D)\) with the mean neighbouring with the debt variable \((D)\), this study thus uses the one-year lagged term of the debt variable \((D)\) for instrumental variable.
The 2SLS IV is first regressed against the GRP growth rate and instrumental variable, which is the one-year lagged term of the debt variable \((D)\) series plus all exogenous variables. At the first stage of the regression, the estimated coefficient of the squared debt term \((D^2)\) is significant at a level of 1 percent, but at the second stage the coefficient of the squared debt term is not significant. For the GMM estimation, when the number of instruments equals the number of parameters, the GMM estimates would coincide with the 2SLS estimates. The GMM addresses the case in which the number of instruments exceeds the number of parameters estimated. As there is only one instrumental variable, the results of the 2SLS IV and the GMM are expected to be identical. The coefficients of the debt variable \((D)\) and squared term of the debt variable \((D^2)\) are -0.15 and -0.14 respectively, but they are not significant. When the Durbin-Wu-Hausman test is applied, the null hypothesis that the debt variable \((D)\) is exogenous is not rejected (Durbin score \(p=0.83\) and Wu-Hausman score \(p=0.84\)), thus there is no evidence that a reverse causal effect exists between local debt and regional growth.
Table 5.6 2SLS and GMM Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>1st Stage SLS</th>
<th>2SLS</th>
<th>GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>-0.150*</td>
<td>-0.150</td>
<td>-0.150</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.150)</td>
<td></td>
</tr>
<tr>
<td>D^2</td>
<td>-1.160***</td>
<td>-0.140</td>
<td>-0.140</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.340)</td>
<td></td>
</tr>
<tr>
<td>lnY LAG(-5)</td>
<td>0.050***</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.840)</td>
<td></td>
</tr>
<tr>
<td>POPG</td>
<td>-1.150***</td>
<td>0.290</td>
<td>0.290</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.570)</td>
<td></td>
</tr>
<tr>
<td>HDI</td>
<td>-0.003**</td>
<td>-0.004</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.720)</td>
<td></td>
</tr>
<tr>
<td>INV/GRP</td>
<td>0.110**</td>
<td>0.063*</td>
<td>0.0630*</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.100)</td>
<td></td>
</tr>
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<td>(0.590)</td>
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<td>Adjusted R^2</td>
<td>0.860</td>
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</table>

Source: Author’s own calculation

Notes: *Significant at 10%, **Significant at 5%, ***Significant at 1%
Numbers in parentheses indicate p-values.

5.5.6 Dynamic Model

This study also adopts a dynamic model to capture the short-term effects of local government debt on regional growth in 33 provinces. In many economic relationships, the dependent variable depends not only on the exogenous variables, but also on its own lagged values (Pasha et al., 2007). This model includes similar dependent and control variables that are used in the baseline model, but a one-year lagged term of the growth rate is also included in the equation as an explanatory variable. The model specification is as
This dynamic model specification has an intuitive appeal in that it allows us to track the short-run effect of GRP-per-capita growth on the overall model. The inclusion of a lagged term might induce a correlation between the lagged dependent variable and the error term, which can be addressed using IV. There are several IV estimators, with Anderson-Hsiao and Arellano-Bond estimators being the most commonly used in existing literature. Use of the Anderson-Hsiao estimator may provide consistent results, but would not be efficient, as it does not take into account all available moment conditions. Arellano and Bond (1991) argue that a more efficient estimator would be produced using additional instruments whose validity is based on the orthogonality between lagged values of the dependent variable and error terms. The GMM approach taken by Arellano and Bond (1991) allows for controlling individual and temporal specific effects with short-run dynamics, solving variable endogeneity bias, simultaneous bias and inverse causality. It has been widely used in short-run dynamic panel data models. In this study, the Arellano and Bond approach is thus implemented for the dynamic estimation.

Table 5.7 presents the GMM results of local debt and regional growth for 33 provinces in Indonesia. The lagged GRP per capita growth has a positive and significant coefficient at the 1 percent significance level across different model specifications. Interestingly, the debt-to-GRP, five-year initial income level and control variables are not significant. Debt-to-GRP and the squared term of debt-to-GRP are mostly significant across different model specifications and they both have negative coefficients suggesting a negative relationship between local debt and regional growth. This confirms the study by (Wu, 2014) that suggested an inverted U-shaped relationship between local debt and

\[ GRPG_{it} = \alpha + \beta y_{i,t-1} + \gamma \ln(Y_{i,t-5}) + \delta D_{it} + \mu_{it} + \varepsilon_{it} \]  

(5.6)
Table 5.7 GMM Estimation Results

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<td></td>
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<td>(0.640)</td>
<td>(0.560)</td>
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</tr>
<tr>
<td></td>
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<td>(0.650)</td>
<td>(0.530)</td>
<td>(0.470)</td>
<td>(0.310)</td>
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Source: Author’s own calculation

Notes: *Significant at 1%, **significant at 5%, ***significant at 10%

Numbers in parentheses indicate p-value.

5.6 Conclusion

This study analyses the impact of local government debt on regional growth and attempts to identify the threshold level of local debt-to-GRP for 33 provinces in Indonesia over the period of 2008 to 2013. To investigate the impact of the ratio of local debt-to-GRP on regional growth, a generalised economic growth model augmented with debt variables is used in the study. The findings suggest that there is a nonlinear relationship between local
government debt and regional growth. The turning point or debt threshold in Indonesia ranges from 55 to 75 percent. The negative coefficient of the quadratic form of local debt-to-GRP suggests a concave or inverted U-shaped relationship between local debt and regional growth. The results also confirm the theoretical assumption that the impact of debt on growth is positive at low debt levels, but beyond the debt threshold an adverse effect on regional growth prevails. Various robustness tests are developed, but the results show that the debt threshold values only marginally differ to the changes of control variables and instrumental variables. There is also no evidence that a reverse causality effect exists between local debt and regional growth in Indonesia.
This thesis has three main focuses. The first is to examine the predictive power of the penalized regression and ANN approach in predicting the incidence of Indonesia's external debt crises. The second is to examine credit cycle characteristics and determinants of the credit booms in Indonesia; and thirdly, the thesis aims to assess the relationship between local government debt and regional growth and determine the optimal level of local government debt to achieve higher regional growth. To achieve these goals, the study brings together several methods, which are based on an analysis of previous and current literature and are used to examine external debt crisis, local government debt and the determination of credit cycle characteristics in Indonesia. A summary of main findings is presented in this section.

6.1 Main Findings

Chapter 2 investigates the ability of a penalized logistic regression to predict the occurrence of external debt crisis in Indonesia. To start, this study uses standard logistic regression, but the results show a separation problem, where one or more predictors may perfectly predict the external debt crisis. This is typical in an environment with a small data set. One variable, the public debt-to-GDP ratio, perfectly predicts the incidence of external debt crises in Indonesia. The penalized regression approach solves this separation problem, and the findings suggest that GDP growth and public debt-to-GDP ratio are among the
most reliable indicators to predict the incidence of external debt crisis in Indonesia. With a
one percent decrease in annual GDP growth, the probability of external debt crises
increases by 63 percent, while an increase in the public debt-to-GDP ratio by one percent
increases the probability of external debt crises by about 80 percent. This confirms the
findings of (Rogoff and Reinhart, 2010) that, in emerging market economies, a high level
of debt is associated with lower growth outcomes and higher level of inflation. Events
study analysis is used to observe the behaviour of macroeconomic indicators during the
times of external debt crisis. It is suggested that short-term debt, debt service, debt maturity
and central government debt increases significantly prior to crisis, as compared to their
values during the normal periods. In the year before a crisis, GDP growth and foreign
reserves show a significant decrease, implying that GDP growth and foreign reserves are
indicators with high predictive power in explaining the instance of external debt crisis.
This chapter uses principal component analysis to reduce a large number of indicators into
fewer numbers of components. The results show that the reserves-to-external debt ratio,
central government debt-to-GDP ratio, inflation and public debt-to-GDP ratio are among
the most reliable indicators in explaining the occurrence of external debt crises.

In Chapter 3, ANN approach is used to predict external debt crisis in Indonesia.
This study uses the ANN method due to its ability to implicitly detect complex non-linear
relationships between the dependent variables of external debt crisis and its covariates.
There are five main covariates used in the study including foreign reserves, exports,
imports, the exchange rate and foreign debt payments. The ANN models with a BP
algorithm are used for correctly predicting in-sample and out-of sample external debt crisis
in Indonesia. The results suggests that the exchange rate, foreign reserves, and exports are
significant contributors to explain external debt crisis in Indonesia, while foreign debt
payments and imports do not play much of role in predicting external debt crisis. The ANN
model can correctly classify crises with 89.12 percent accuracy. For out-of-sample
prediction, the performance is not as robust as the in-sample prediction. It is argued that the ANN model tends to over-fit the data for in-sample prediction, while it cannot fit the out-of-sample very well. The 10-fold cross validation is used to improve the out-of-sample prediction accuracy, and the performance of the ANN with 10-cross validation has improved reasonably well. The out-of-sample performance is sensitive to the size of the samples, as it yields a higher total misclassification error and lower prediction accuracy. It is suggested that the ANN model has been effectively used to identify past crisis episodes with some high degree of accuracy, but predicting crises outside the estimation samples is more challenging due to a higher rate of false alarms and any other uncertainties that may also present.

In Chapter 4, the examination of the characteristics of the credit cycle in Indonesia produced some interesting findings. The findings suggest that Indonesia experiences more episodes of credit booms than credit busts. When credit booms took place, they persist for longer, and are followed by credit busts, which are short-lived and deeper. The results confirm the findings of Dell’Ariccia et al. (2016) which show that credit booms tend to be larger and last longer than credit busts. This chapter also demonstrates a significant and positive relationship between credit growth and new credit approval to credit booms in Indonesia. A rapid credit growth and higher new credit approval ratio not only contributes to the possibility of a credit boom, but also to the magnitude of the credit boom. The results also find that a lower policy rate increases the likelihood of a credit boom. For the magnitude of a credit boom, the residential house price index, inflation, and GDP growth are also significant determinants. An increase in the residential house price and GDP growth increases the magnitude of the credit boom, while a rise in inflation decreases the magnitude of the credit boom.

Chapter 5, this chapter aims to extend the work of Wu (2014) by presenting an empirical analysis of relationship between local government debt and regional growth for
the case of Indonesia. The significance of the study lies primarily in its importance to determine the optimal point of local debt at which local government can achieve higher regional growth. This chapter analyses the impact of local government debt on regional growth and attempts to determine the threshold level of local debt-to-GRP for 33 provinces in Indonesia over the period between 2008 and 2013. Using a generalized economic growth model augmented with debt variables, the results show a non-linear and inverted U-shaped relationship between local government debt and regional growth. It is suggested that low levels of borrowing will positively impact the regional growth, but when a certain threshold is passed, it will adversely impact regional growth. The turning point or debt threshold for local government debt in Indonesia is found in the 55 to 75 percent range. There is also no evidence that a reverse causal effect exists between local government debt and regional growth.

6.2 Policy Implications

The findings of the study reveal and suggest a few policy implications for governments specifically for external debt management. Indonesia should be brought to a more manageable external debt level and sustainable level of economic growth, as the findings suggest that public debt-to-GDP ratio and GDP growth has an instrumental role on external debt crises. Prudent management of external debts is necessary, and the government should implement policies to create sustainable long-term economic growth that will increase revenue generation and investment, increase employment and reduce the poverty level. To mitigate the adverse impact from excessive external debt levels, there is also a need to lessen the amount of external debt to a more manageable level. Foreign borrowings increase vulnerability to external conditions, for example, when external debt is at floating
rate, a higher foreign interest rate can lead to an increase in debt-servicing cost and raise budget expenses that can be translated into a higher budget deficit. Having a more balanced proportion of debt towards domestic debts can be preferable, as the potential cost from the exchange rate risk may be exacerbated. Even though domestic debts may have a higher cost than external debts, it can actually encourage further development of domestic debt markets. In the medium and long term, the development of these markets can lower the cost of access to domestic financing.

With regard to credit cycles, Indonesia’s central bank and government should be aware that the country experiences more episodes of credit boom than credit bust. When credit booms occur, they persist longer, but will be eventually followed by credit busts that are short-lived and deeper. While strong economic growth, low interest rates or an increase in housing prices may be good for the economy, they can actually increase the possibility of a credit boom and subsequent credit crisis. The government should make efforts to fully understand this situation, considering the cost of credit crises are huge and also have detrimental impacts on the economy and the country as a whole.

In relation to local government debt, one important implication of a negative nonlinear relationship between local government debt and regional growth is that the local governments need to understand that the local debt will only be productive up to a certain level, but beyond this threshold, the impact may be counterproductive. More importantly, as the level of local debt remains very low in Indonesia, there is ample room for the local governments to utilize local debt instruments to finance various local infrastructure projects which could achieve higher regional growth.
6.3 Suggestions for Future Research

This study focuses mostly on the past and current external debt crises, exploring particularly the implications of the different phenomena on the external debt crises in Indonesia. There is a need for future research focussing on the examination and evaluation of policies that the government should put in place to control rising external debt problems. In effect, the government of Indonesia has been more reactive, rather than proactive, especially when formulating strategies to deal with the external debt crises in the past. The evaluation of various external debt reduction policies can provide a road map for the country to adopt the most appropriate policy interventions to curb external debt crises.

This study also examines the usefulness of the ANN model in predicting external debt crises in Indonesia. While the ANN model is highly useful in correctly predicting and classifying crises, the out-of-sample performance is not as robust as performance of the in-sample prediction. In this respect, the ANN model seems to over-fit the data for in-sample prediction, while under-fitting out-of-sample data. Future research, therefore, needs to focus on using the ANN model with larger sample sizes to more accurately predict the likelihood of debt crisis. More importantly, there is a need to have an ANN model that is able to more accurately predict crises outside the estimation samples. Also, it is imperative that the new ANN model should produce minimal instances of false alarms.

In estimating the credit cycle, it is also important to understand the motivations and behavioural aspects of economic actors that drive overexpansion and contraction of credit over cycles, for example, the motivation of the central bank to pursue low interest rate policy; or what factors households or firms consider when taking out credit from the bank. This can be achieved through experimental studies or survey methods; thus a big picture view and underlying reasons behind the fluctuations of credit variables over the credit cycles can be better understood.
This study also reports on the relationship between local government debt and regional growth in Indonesia. It is revealed that the relationship is an inverted U-curve, where, to a certain level, an increase in the local debt will increase regional growth, but beyond a certain threshold, its impacts are counterproductive. As this study uses local government enterprise (BUMDs) debts as a proxy to reflect total local debts (as BUMD debts constitute to about 70 percent of total local debts), future research needs to use more comprehensive local debt data, collected over a longer time period.
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