UNDERSTANDING INDONESIA'S EXTERNAL DEBT CRISIS:
A PENALIZED LOGISTIC REGRESSION APPROACH

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Abstract

In this study, we applied Firth's penalized logistic regression to examine Indonesia's external debt crisis. The penalized regression method could be effectively used to solve a separation problem that can frequently occur in small data sets. Our results for a standard logistic regression show that a separation problem occurs where one or more variables could perfectly predict a debt crisis. The penalized regression results show that GDP growth and public debt to GDP ratio are among the most significant indicators to predict a debt crisis. The probability of a debt crisis occurring increases by 63 per cent with a 1 per cent decrease in annual GDP growth, while an increase in the public debt to GDP ratio of 1 per cent will increase the probability of a debt crisis occurring by around 80 per cent. These confirm the findings of Reinhart and Rogoff (2010) that in emerging market economies, a high level of debt is associated with lower growth outcomes and a significantly higher level of inflation.

Keywords: debt crisis, external debt, penalized logistic regression

JEL Classifications: C53, G01, H63

1. Introduction

Despite the emergence of a growing literature on early warning systems for financial crises, the determinants of a debt crisis for an individual country are yet to be fully understood. This paper identifies macroeconomic and debt indicator characteristics during times of crisis and applies a penalized logistic regression for debt crisis prediction to reduce biased estimation parameters in the standard logistic regression.

Previous studies using data for both developed and developing economies have examined the usefulness of macroeconomic and debt indicators to predict an external debt crisis, but 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 than a standard logistic regression model is due to the limited number of observations and the separation problem that occurred in our small data sets. The main finding is that some macro indicators have a very high predictive power for debt crises and the penalized regression model can be effectively used in a small data set environment.

The paper proceeds as follows. Section 2 contains a literature review including definitions of a debt crisis and existing studies in the prediction of debt crises. Section 3 describes the penalized logistic regression model. Section 4 describes empirical analysis including data description and data processing; in this section, an analysis that is used to observe the behavior of indicators in the event of a crisis is also discussed, as well as principal component analysis. Section 5 discusses the results. Section 6 draws the conclusion.

2. Literature Review

Early warning systems for debt crises mainly consist of three major aspects: definition of debt crisis, the choice of methods, and covariates. The purpose of this section is to provide a review of the existing literature that examines how these aspects apply to the development of early warning systems for debt crises. The findings of this study provide a useful background to determine the major factors and choice of econometric model for a debt crisis that will be presented in the Section 3.

2.1 Definitions of debt crisis

There is no single definition of an external debt crisis. Pescatori and Sy (2007) classify a debt crisis as sovereign default, large arrears, large IMF loans, and distress events.

Debt crises as sovereign default

Rating agencies mainly focus on default events and use the degradation of credit ratings scores as a proxy for the heightening probability of default. Moody's Investor Service (2003) defines a sovereign default as occurring when there is either a missed or delayed disbursement of the interest and/or principal, or a distressed exchange occurring where the issuer offers bondholders a new security or package of securities with diminished financial obligation, such as new debt instruments with a lower coupon or par value.

Standard & Poor's defines 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 default when either scheduled debt service is not paid on the due date or when an exchange offer of new debt contains less favorable terms than the original issue. For central bank currency, default occurs when notes are converted into new currency of less-than-equivalent face value, and for bank loans, when either scheduled debt service is not paid on the due date or a rescheduling of the principal and/or interest is agreed to by creditors at less-favorable terms than the original loan.

Reinhart et al. (2003) used debt crises derived from S&P definition and found 36 episodes out of 53 debt crises in emerging countries between period 1970 and 200. According to Beim and Calomiris (2001), a country is in debt default if all or part of interest and/or principal payments due are reduced or rescheduled.

Debt crises as large arrears

Detragiache and Spilimbergo (2001) classify a country as being in a debt crisis if the country has arrears on external obligations to commercial creditors of more than 5 per cent of total arrears for principal and/or interest payments. The authors 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 using 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 official and private creditors of more than 2 per cent of total external debt; or the total amount of long-term debt rescheduled in any given year exceeds 2.5 per cent of total external debt.

De Paoli and Saporta (2006) define a debt crisis as occurring when a country has large debt arrears (on principal or interest payments) or 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 per cent or 5 per cent respectively.

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 Standard & Poor’s or if it receives a large non-concessional IMF loan, that is, an access in excess of 100 per cent of quota. Standard & Poor’s rates sovereign issuers 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.

Debt crises as distress events

Sy (2004) defines debt crises as situations of sovereign distress when the average spreads on the most liquid sovereign bonds are above 1000 basis points of US Treasury Securities. The choice of the 1000 bps gap above the US Treasury as a threshold is considered to be a psychological barrier by market participants.

Other definitions of debt crisis

Kraay and Nehru (2004) define debt crisis episodes in which countries resort to any of the following: substantial arrears on their external debt, debt relief from the Paris Club of creditors, or non-concessional balance of payment supports from the International Monetary Fund (IMF).

Cohen and Valadier (2011) have modified the definition of debt distress proposed by Kraay and Nehru (2004). A country is said to experience a debt crisis when either of the following conditions are met: the total arrears of principal and interest on long-term debt to all creditors exceed 5 per cent of the total debt outstanding; or a country receives debt reliefs from the Paris Club or receives a significant balance of payment supports 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. They used a solvency ratio indicator of external debt for their early warning systems. The solvency ratio of external debt is defined as current account plus capital account over principal and interest payment and is used as a proxy for an economy’s ability to repay its overseas debts to non-resident lenders.

As noted in the introduction, we will define an external debt crisis as occurring when either large arrears on external obligations of more than 5 per cent of total debt stocks (Detragiache and Spilimbergo, 2001; De Paoli and Saporta, 2006; Cohen and Valadier, 2011; Kraay and Nehru, 2004; Ciarlone and Trebeschi, 2005) or a rescheduling or restructuring agreement into less favourable terms to lenders than in the original arrangement (Reinhart and Rogoff, 2010; Chambers and Alexeeva, 2003; Ciarlone and Trebeschi, 2005).

2.2 Existing Studies

There is a large body of literature on methods used for predicting debt crises, including logistic regression models (Ciarlone and Trebeschi, 2005; Fuertes and Kalotychou, 2007; Manasse et al., 2003), binary recursive trees (Manasse et al., 2003; Manasse and Roubini, 2009), and, more recently, methods of Artificial Neural Networks (Fioramanti, 2008).

Each early warning system (EWS) method has its own advantages and drawbacks. The main advantage of the logistic model is that it enables the measurement of the effect of each explanatory variable on the crisis probability. It is most suited to predict a binary outcome from a vector of explanatory variables. The logistic regression model is parametric; it generates confidence intervals for the coefficient values. The logistic regression, however, also 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 also restricted to the discrete number set. It also relies heavily on large samples, while small sample sizes can lead to inaccurate estimates of parameters.

The binary recursive tree displays a number of features. The methodology 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. The missing values for predictors could also be handled very effectively, and the interpretation of the binary tree is intuitive. The model output is represented as a tree that is split according to threshold values of the variables that are deemed to be important contributors to the crises.

Artificial Neural Network (ANN) methods, albeit popular and predominantly used in the fields of science and engineering, have received relatively little attention in economics and finance. ANNs have been used to construct EWS for debt crisis prediction (Fioramanti, 2008). In his studies, the author showed that the ANN model outperforms traditional logistic regression under certain conditions. The flexibility of neural networks and their ability to approximate non-linear relationships are considered the major advantages of this model.

In this study, we will apply penalized logistic regression to estimate parameters of debt crisis based on Firth estimation (Firth, 1993). The rationale to apply a penalized regression into our model is due to limited number of observations (42 observations, 1970-2012). This method could be effectively used to solve the separation problem that frequently occurs in small data sets. The standard logistic regression often results in a separation problem when one or more variables could perfectly predict the data. In the penalized regression, we will maximize the log likelihood 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 more heavily.

3. Penalized Logistic Regression Model

Logistic regression provides a good method for classification by modelling the probability of membership of a class with transforms of linear combinations of explanatory variables. However, a standard logistic regression may not work when there are far more variables than observations. Particular problems that might emerge are multicollinearity and over-fitting. One possible solution is to apply penalized logistic regression.

Consider a standard linear regression model as follows:

$$Y = X\beta + \varepsilon \tag{1}$$

Where Y is a $n \times 1$ matrix of dependent variables; X is a $n \times m$ matrix of explanatory variables; β is a $m \times 1$ matrix of parameters; and ε is a $n \times 1$ matrix of errors**.** The regression coefficients are estimated by minimizing:

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

Which leads to:

$$\hat{\beta} = (X'X)^{-1}X'Y \qquad (3)$$

A large m may lead to serious 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 (no bias but high variance). This could be misleading because large variability in the estimates produces a prediction formula for discrimination with almost no power (Antoniadis, 2003).

The key idea in penalization methods is that over-fitting is avoided by imposing a penalty on large fluctuations in the estimated parameters:

$$S_n(\beta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \sum_{j=1}^{m} x_{ij\beta_j})^2 + \lambda J(\beta) \qquad (4)$$

Where $J\ (\beta)$ is a penalty that discourages high values of the elements of β.

In generalized logistic regression, we can rewrite logistic regression formula as follows:

$$y_i = \frac{p_i}{1-p_i} = \alpha + \sum_{j=1}^{m} x_{ij}\beta_j \qquad (5)$$

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.

Penalized Maximum Likelihood Estimation (Firth estimation)

Firth (1993) introduced an algorithm of penalized regression to address issues of separability, small sample sizes, and bias of the parameter estimates. In logistic regression, when the outcome has low (or high) prevalence, or when there are several interacted categorical covariates, all the observations could have the same event status. A similar event occurs when continuous covariates predict the outcome too perfectly. This phenomenon is known as separation (including complete and quasi-complete separation) and will cause problems by over-fitting the model. Sometimes the only symptom of separation will be extremely large standard errors, while other times, software may 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 more detailed analyses with separable data sets.

Consider the following logistic regression model:

$$P(y_i = 1|x_i, \beta) = \pi_1 = \{1 + \exp(-\textstyle\sum_{r=1}^{k} x_{ir}\beta_r)\}^{-1} \qquad (6)$$

Where $(y_i, x_i), y_i \epsilon \{0,1\}, i = 1,2 \dots n$ denotes a sample of observations of dependent variable *y* and the vector of independent variables with the dimension of $1 \times k$.

Maximum likelihood estimates for the regression parameter, intercept, and slopes $\beta_r, r = 1,2 \ldots k$ are found by solving the k score equations:

$$\frac{\partial \log(L)}{\partial \beta_r} = U(\beta_r) = 0 \qquad (7)$$

Where L is the likelihood function. In order to reduce the sample bias of these estimates, Firth (1993) suggest the estimation of a modified score equation:

$$U(\beta_r)^* = U(\beta_r) + \frac{1}{2}\mathrm{trace}[I(\beta)^{-1}\{\partial I(\beta)/\partial \beta_r\}] = 0 \ \ (r=1,\ldots,k) \qquad (8)$$

Where $I(\beta)^{-1}$ 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.

The STATA (version 12.0) of Firth's module will be used to run penalized regression estimation. The separation problem and biased estimations could be successfully eliminated with Firth-type estimation instead of maximum likelihood estimation. The aim of this study is to apply Firth logistic regression to reduce biased estimation when a separation problem occurs in predicting debt crisis in Indonesia.

4. Empirical Analysis

4.1 Data description

The primary sources of data for the analysis are the World Bank External Debt statistics and the World Bank database. Important information on macro indicators that was not reported in the above publication was collected from the International Financial Statistics of IMF. Data were compiled based on 43 observations from 1970 to 2012.

Our external debt crisis as the dependent variable was derived from data provided by the External Debt statistics of the World Bank. We defined a debt crisis as the event when either a country has large arrears on external obligations towards commercial creditors, or when a country has rescheduled or restructured their debt agreement with commercial creditors.

Indonesia had large arrears on their external debts over the period from 1998 to 2004, and has rescheduled or restructured their external debt agreements from 1998 to 2003 and in the year of 2005. Therefore, we assumed debt crises have occurred from 1998 to 2005. As crisis is a binary output variable, we assigned crisis year as 1 and 0 otherwise (non-crisis).

The choice of covariates was largely drawn from the existing literature. The theoretical literature highlights a variety of factors that could trigger a debt crisis. Measures of debt solvency, such as debt-to-GDP ratio, and measures of liquidity, such as short-term debt to reserves or exports and debt service to reserves or exports, are significant explanatory variables, as are macroeconomic indicators such as GDP growth, inflation, currency overvaluation and fiscal balance (Manasse et al., 2003). Detrachiache and Spilimbergo (2001) found that short-term debt, debt service and reserves are among significant indicators that have high predictive power leading to debt crisis. Ciarlone and Trebeschi (2005) used variables drawn from debt sustainability measures including debt burden, debt service, reserves, macro indicators and net capital flows. Fioramanti (2008) mainly used macro indicators (GDP growth, inflation, interest rate, currency overvaluation) and debt measures (short-term external debt, interest on external debt, total external debt and average debt maturity) in their EWS model.

In this study, we applied various covariates into our EWS model that could form a backbone in an attempt to predict debt crisis (Table 1). The first variable (x1) is the average debt maturity. Maturity is the number of years to 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 principal. The repayment period is the period from the first to last repayment of principal. To obtain the average, the maturity for all public and publicly guaranteed loans has been weighted by the amounts of the loans. When a country has a debt structure in which a large portion of its debt matures in the short-term, it is more likely for that country to find difficulties to service its debt.

Table 1 List of Variables

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

Our other variables of interest 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). Total interest payment is the sum of interest actually 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 higher portion of interest payments relative to exports, most of export revenues will be allocated for debt repayment, reducing the country's financial position.

The indicator of short term debt as a percentage of total external debt (x4) could be used to reflect the problem of increased illiquidity and insolvency of a country in the short-run. The main reason to include this indicator is that in many instances of debt crisis, short-term debt has increased significantly in the lead-up to the crisis. Short-term debt includes all debts with 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 non-guaranteed long-term debt; the use of IMF credit; and short-term debt.

The inclusion of total debt service relative to export of goods and services (x5) that measures the debt servicing obligation of a country and could give a useful signal in predicting a debt crisis, is consistent with the views that some recent debt crises were experienced together with illiquidity and insolvency problems. The total debt service is the sum of principal repayments and interest actually paid in currency, goods, or services on long-term debt; interest paid on short-term debt; and repayments (repurchases and charges) to the IMF.

The indicator of total reserves to GDP (x6) measures the extent to which foreign reserves such as foreign exchange reserve, SDR or gold are available to service debt. In times of crisis, stock of reserves is generally deteriorated due to a weaker balance of payment. A lower ratio of reserves to GDP is an indication that the country may find it difficult to service its debt. Total reserve comprises holdings of monetary gold, special drawing rights, 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 ratio of public debt to GDP (x8) are other variables of interests. The higher ratio of either central government debt to GDP or public debt to GDP could provide an indication that the large amount of debt might be counterproductive for the economy and impact a country’s ability to repay its debt. The central government debt is the entire stock of direct government fixed-term contractual obligations to others which are outstanding 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, while 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 to service their debt is the foreign exchange generated by exports of goods and services; therefore, we consider the ratio of exports of goods and services relative to GDP (x9) as a useful indicator for our model. It is also reasonable to assume that a high level of exports makes it less likely that a country has large arrears on their debt or a need to reschedule or restructure their debts. In other words, a high level of exports of goods and services will increase foreign exchange earnings and reserves to meet debt service obligations.

The domestic indicators of inflation (x10), annual GDP growth (x11) and real interest rate (x12) are some of the important variables that are widely used in the early warning system literature. Most developing countries have been in a constant attack of inflation in the recent past. If inflation is present, part of the amortization of a loan will be transferred in the form of interest. There is another channel through which inflation may affect the availability of foreign exchange. As domestic prices increase in times of high inflation, it reduces a country’s competitiveness thus simultaneously reducing exports. Foreign reserves are depleted, resulting in either large debt arrears or debt rescheduling/restructuring. With regards to GDP growth, the underlying assumption to include this variable in the model is that in times of strong GDP growth, the expansion of goods and services produced domestically could increase aggregate demand. In this situation, supply of exports of goods and services would potentially increase, while the demand for imports would decline. The current account and balance of payment positions will be stronger, which is beneficial to a country's ability to service its debt. As for the real interest rate, it indicates the extent to which a country is vulnerable to increases in interest rates charged by private creditors, especially banks. In times of a high positive real interest rate, it will result in increased payment obligations. In such cases, it will compel debtor countries 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 booms, 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 to the economy, as it might create over-heating in the economy that might trigger a crisis.

The change in the money supply (x14) is measured as the difference in end-of-year totals relative to the level of M2 in the preceding year. Money and quasi money (M2) comprise 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 high inflation prevails, domestic prices increase and will eventually reduce exports and competitiveness. This will cause a deterioration of the balance of payment, resulting in adverse impacts for debt servicing.

The fiscal indicator of cash surplus to GDP (x15) provides a useful indication of a government's need to call on 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 expenses and minus net acquisition of nonfinancial assets.

It is suggested to apply data rescaling to the data set before processing the data further (Famili et al., 1997). We rescaled all original variables using normalization and standardization methods. The objective of the data rescaling is to eliminate the difference in magnitudes that may affect the robustness of the result. Rescaling is important when dealing with parameters of different units and scales, thus ensuring that all parameters will have the same scale for a fair comparison between them.

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

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{9}$$

In the standardization, we transformed data in such way to have zero mean and unit variance. The formula for standardization is as follows:

$$x_{new} = \frac{x - \mu}{\sigma} \tag{10}$$

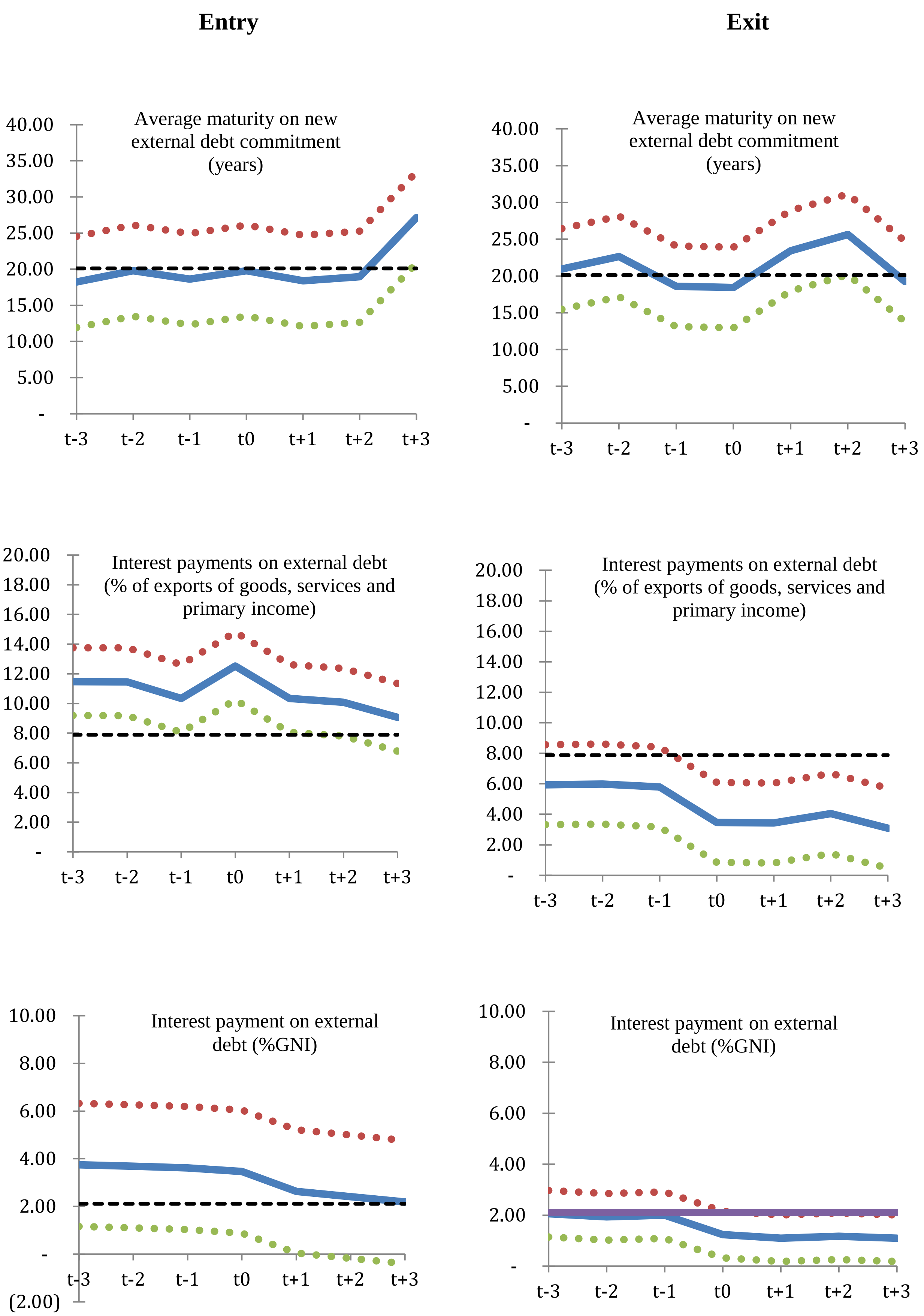
We applied both normalization and standardization to our data set, as our data have different units and scales. Normalization has a strong ability to handle data sets with outliers, while standardization is more appropriate for use when data are normally distributed.

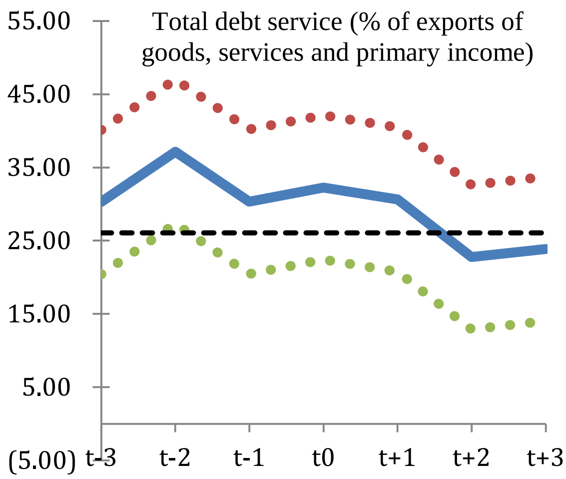
4.2 Event Study Analysis

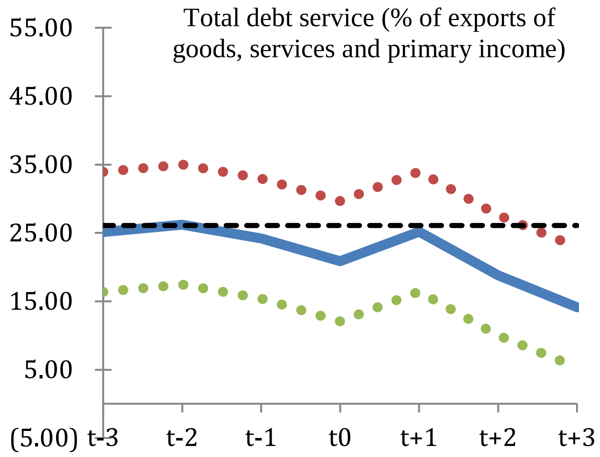
We first applied event study analysis to provide some understandings about the behavior of covariates around the time of crises[†]. The results of event study are shown in Figure 1; the dashed black horizontal line represents the average value during non-crisis periods, while the solid blue line shows the average value of the variable during crisis time with a 95 per cent confidence interval, represented by the dotted lines. The period goes from t-3 to t+3, where t is the year in which the external debt crisis occurred (y=1), thus signaling a crisis entry. The three year crisis window was chosen as it would sufficiently describe the behavior of each indicator around the debt crisis. For example, for other types of crisis, such as a balance-of-payment crisis, windows are defined as the 24 months preceding and following the crisis, while banking crisis windows are defined as the 12 months before and after the crisis (Kaminsky and Reinhart, 1999).

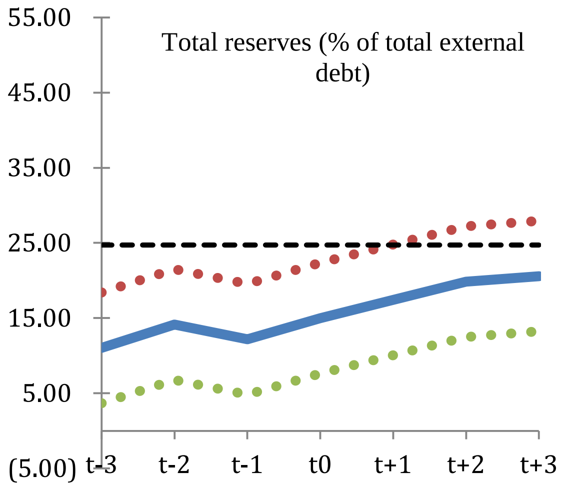
[†]The event study figures were performed through regression of the respective explanatory variables on a set of seven dummies variables for the three years preceding the crisis (crisis entry), the crisis itself, and the three years following the crisis (crisis exit). The estimated constant was the mean of all non-default episodes, shown as the dashed horizontal line. The estimated coefficient on the dummies provided the difference from the non-default episode mean to the respective event (crisis entry or exit). Therefore, the mean for the respective event episode was computed by adding the estimated constant and the estimated coefficient on the dummy. The confidence interval indicate whether mean of the event is significantly different from the non-crisis means was 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).

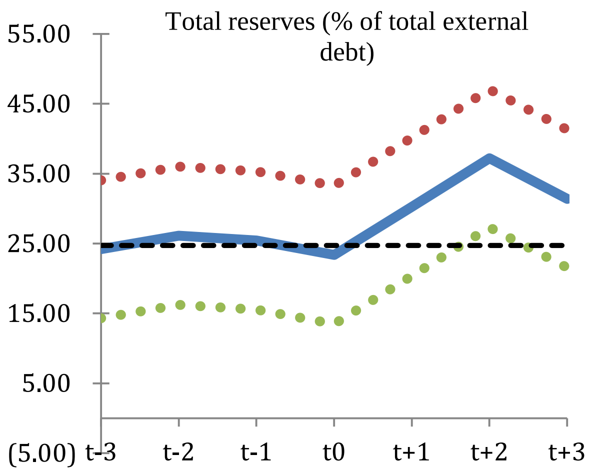
Figure 1 Result of Event Study Analysis

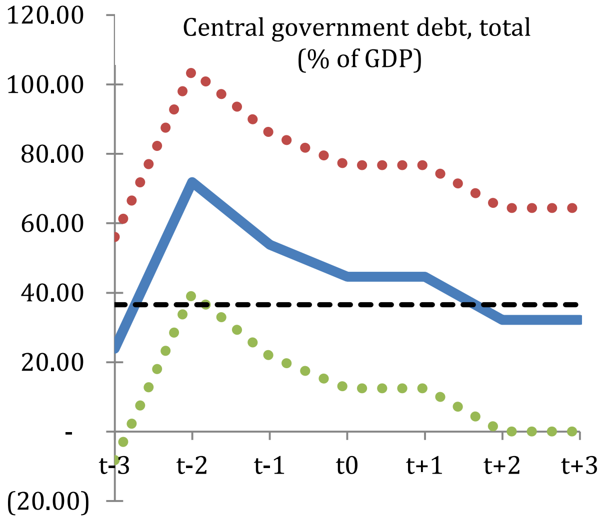


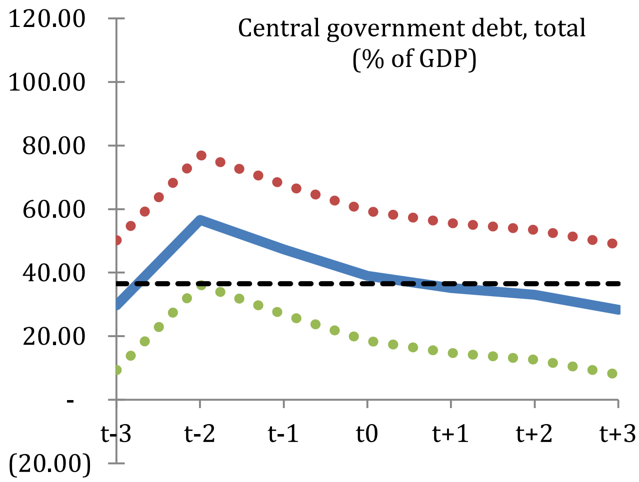

Total debt service (% of exports of goods, services and primary income)
55.00
45.00
35.00
25.00
15.00
5.00
(5.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3


Total debt service (% of exports of goods, services and primary income)
55.00
45.00
35.00
25.00
15.00
5.00
(5.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3


Total reserves (% of total external debt)
55.00
45.00
35.00
25.00
15.00
5.00
(5.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3


Total reserves (% of total external debt)
55.00
45.00
35.00
25.00
15.00
5.00
(5.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3


Central government debt, total (% of GDP)
120.00
100.00
80.00
60.00
40.00
20.00
-
(20.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3


Central government debt, total (% of GDP)
120.00
100.00
80.00
60.00
40.00
20.00
-
(20.00)
t-3
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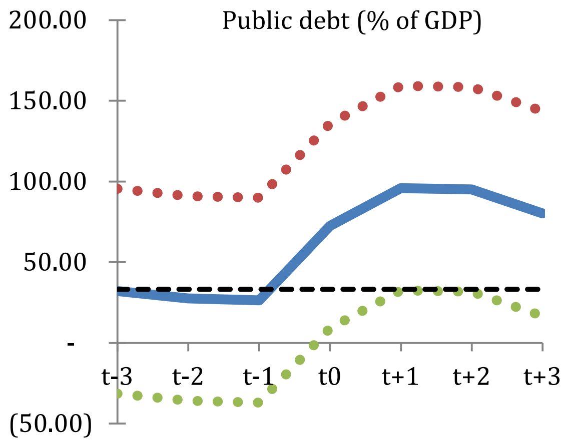
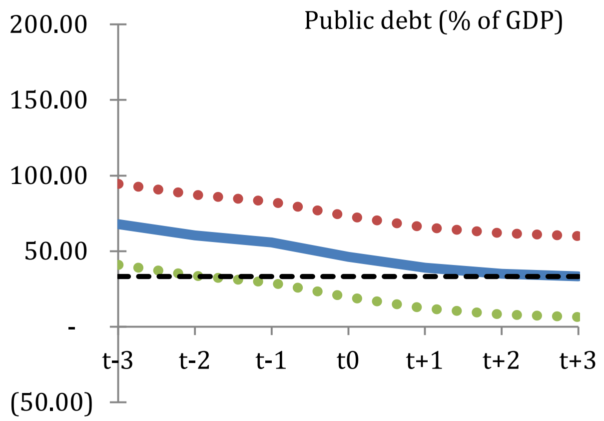
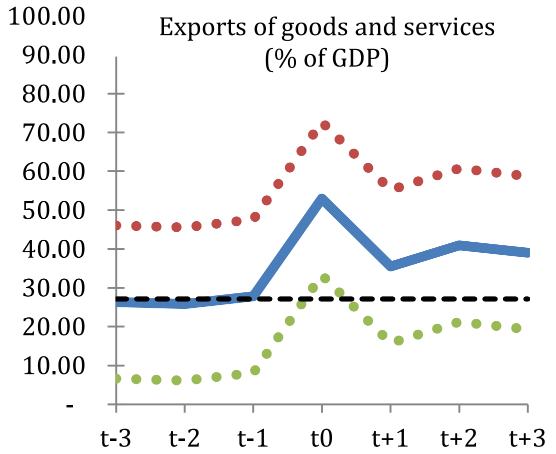
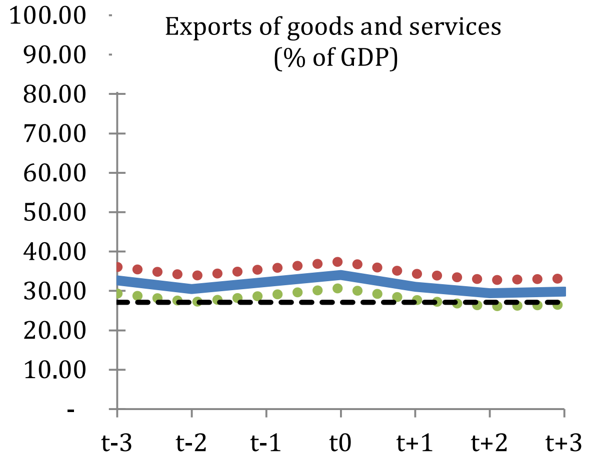
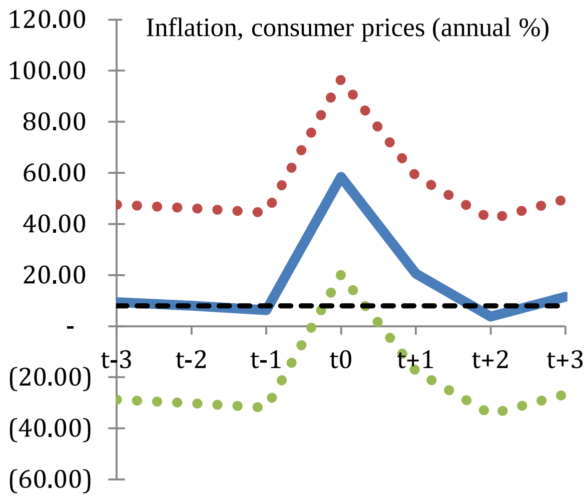
t0
t+1
t+2
t+3

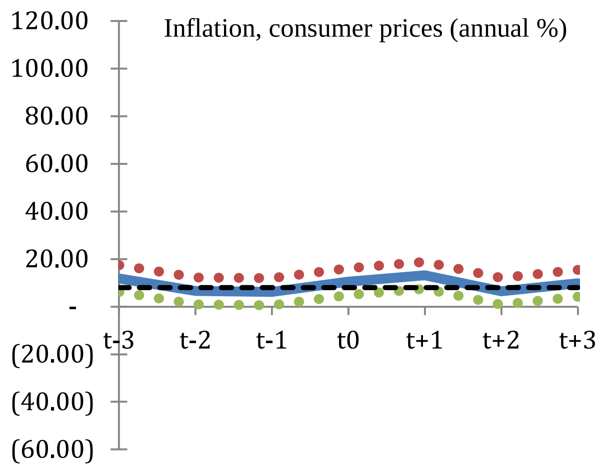

Public debt (% of GDP)
200.00
150.00
100.00
50.00
-
(50.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

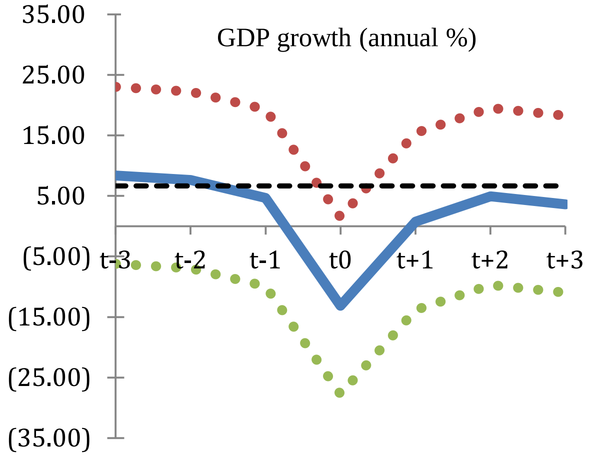

Public debt (% of GDP)
200.00
150.00
100.00
50.00
-
(50.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

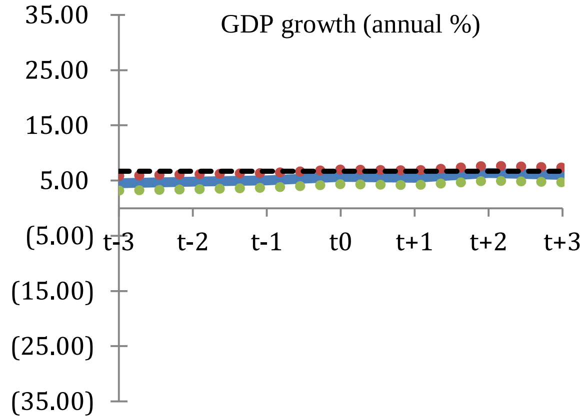

Exports of goods and services
(% of GDP)
100.00
90.00
80.00
70.00
60.00
50.00
40.00
30.00
20.00
10.00
-
t-3
t-2
t-1
t0
t+1
t+2
t+3

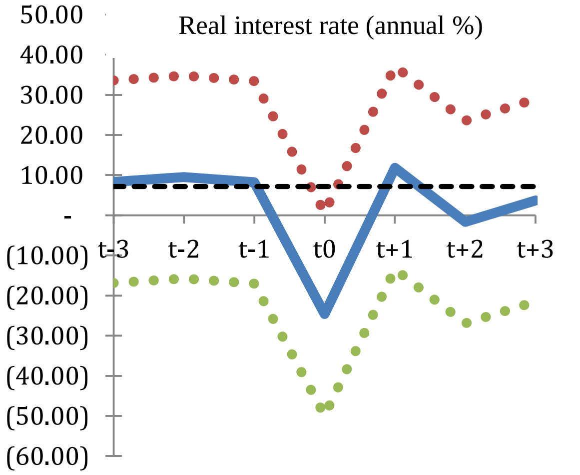

Exports of goods and services
(% of GDP)
100.00
90.00
80.00
70.00
60.00
50.00
40.00
30.00
20.00
10.00
-
t-3
t-2
t-1
t0
t+1
t+2
t+3

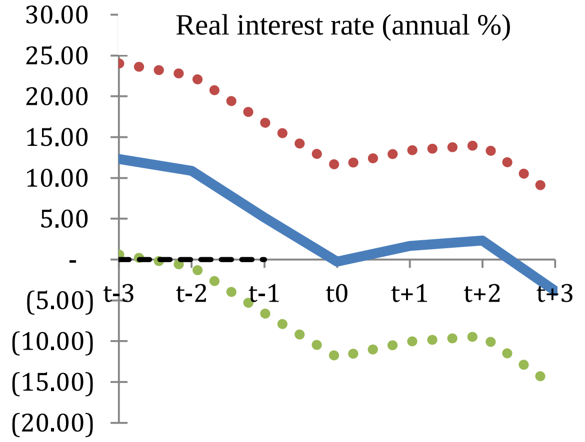

Inflation, consumer prices (annual %)
120.00
100.00
80.00
60.00
40.00
20.00
-
(20.00)
(40.00)
(60.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

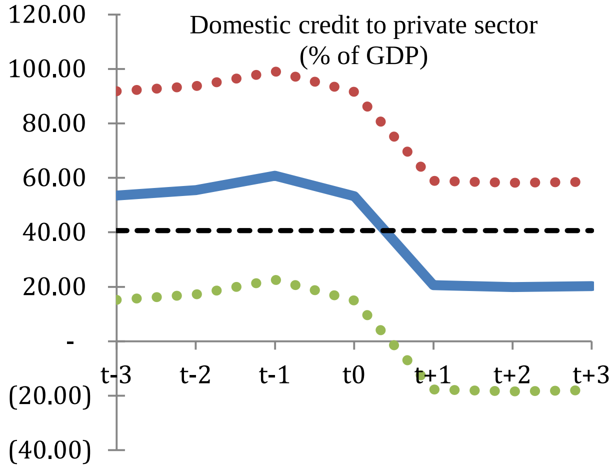

Inflation, consumer prices (annual %)
120.00
100.00
80.00
60.00
40.00
20.00
-
(20.00)
(40.00)
(60.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

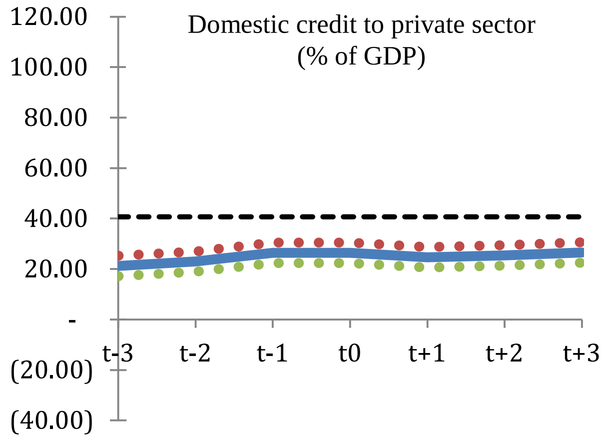

GDP growth (annual %)
35.00
25.00
15.00
5.00
(5.00)
(15.00)
(25.00)
(35.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

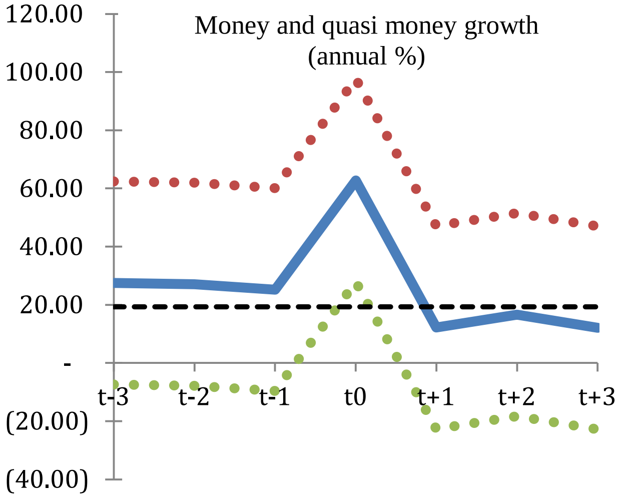

GDP growth (annual %)
35.00
25.00
15.00
5.00
(5.00)
(15.00)
(25.00)
(35.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

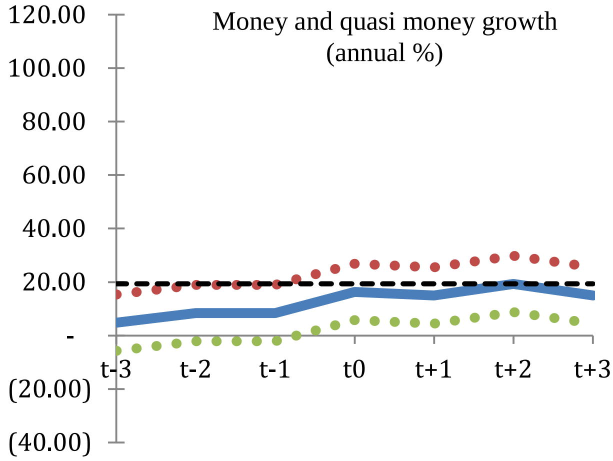

Real interest rate (annual %)
50.00
40.00
30.00
20.00
10.00
-
(10.00)
(20.00)
(30.00)
(40.00)
(50.00)
(60.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

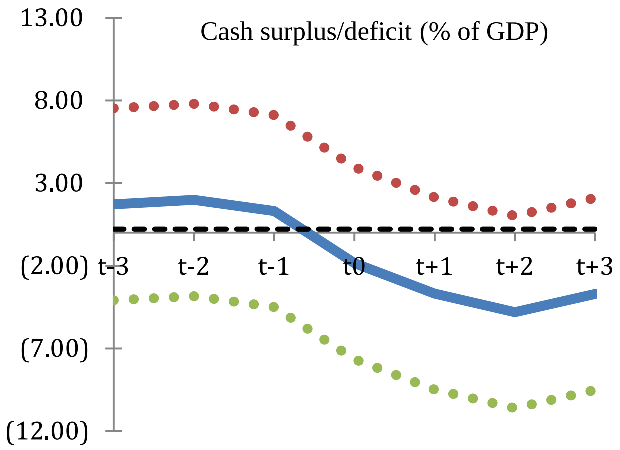

Real interest rate (annual %)
30.00
25.00
20.00
15.00
10.00
5.00
-
(5.00)
(10.00)
(15.00)
(20.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3

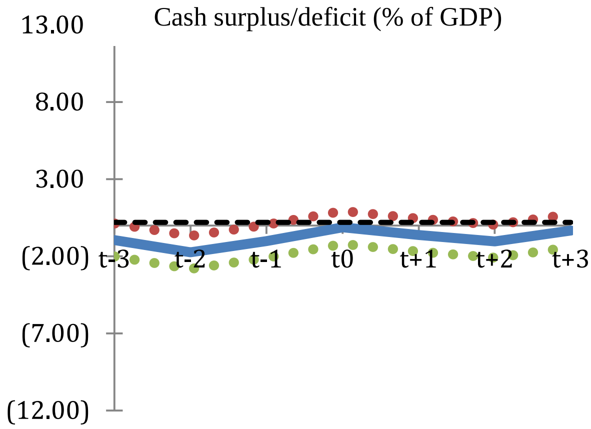

Domestic credit to private sector
(% of GDP)
120.00
100.00
80.00
60.00
40.00
20.00
-
(20.00)
(40.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3


Domestic credit to private sector
(% of GDP)
120.00
100.00
80.00
60.00
40.00
20.00
-
(20.00)
(40.00)
t-3
t-2
t-1
t0
t+1
t+2
t+3









The event study suggests that the measures of external debt were significantly different during crisis periods with respect to the 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 were higher than their average value during tranquil times. In the year following the crisis (exit), those indicators were moderated toward their historical averages.

One interesting observation is the behavior of GDP growth before the crisis. There was a significant decrease in the GDP growth in the year prior to the crisis, suggesting that GDP growth might be considered as one of the main indicators that could predict future debt crises. Inflation also rose significantly in the year before the crisis. Our event study results confirm the studies of Manasse (2003) and Ciarlone and Trebeschi (2005).

4.3 Principal Component Analysis

We also applied principal component analysis (PCA) to detect whether some underlying patterns of relationships exist among our covariates. In the PCA, a number of covariates could be reduced into a set of principal components less than the original covariates. The PCA helps explain as much information of original covariates as possible by extracting some 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 our observations were also limited, the PCA could help reduce the dimension of parameters and thus decrease the degree of freedom in our model. The principal component may be expressed as:

$$x_{i,k} = \; a_{i1}C_1 + a_{i2}C_2 + \cdots + a_{ik}C_k \tag{11}$$

where each of the *n* observed variables (x_i) is described as the linear combination of the *k* components C_1, $C_{2,\dots,}C_k$; and a_{ik} is the factor loading (regression weight) on the k^{th} component.

The first component maximized the variance it has explained, while the subsequent components accounted for the entire variance. The most important components are those which have higher contribution to the total variance and they usually have eigenvalue greater than 1.0, while components with eigenvalue less than 1.0 only explain a small portion of variance and many times are excluded.

The components were extracted in such a way as to ensure that one component is independent of the others, i.e. components are orthogonal, and the loadings of such components are referred to unrotated components. To obtain terminal solutions, the unrotated components were rotated by maximizing the variance of squared loadings. In this study, we used the variance of orthogonal rotation (varimax).

In our study, we reduced 15 variables into several principal components retaining most information of original variables. We also conducted scenario analysis using different numbers of principal components and compared them in terms of total variance explained.

We used 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). From this test, we looked at a small *p*-value indicating that it is highly unlikely to obtain the observed correlation matrix from a population with zero correlation. The result showed an associated *p*-value of 0 and thus we rejected the null hypothesis. Applying normalization and standardization rescaling methods, we had similar KMO value of 0.539, greater than the suggested value of 0.5.

Table 2 shows cumulative percentage of variance explained for different numbers of principal components. Higher numbers of principal components explain more variation than fewer components. Applying the rescaling methods of normalization and standardization, we had similar a figure of the percentage cumulative variance explained.

Table 2 The Percentage of Cumulative Variance Explained

Rescaling method	**#Principal components**	**% Cumulative variance explained**
Normalization/ Standardization	4	88.28
	5	93.33
	6	96.32
	7	98.06

Source: author's own estimates

We rotated the component matrix using the varimax rotation method, an orthogonal rotation with Kaiser Normalization to obtain optimal solutions. As we were only concerned with variables with high degrees of correlation, we removed variables with correlation less than 0.4.

With regards to the rotation matrix, we only selected the top variables with variance greater than 0.85 for each component. We chose internal payment on external debt (x2), total debt service (x5) and reserves to external debt (x6) as the most significant variables for the first component. For the second component, inflation (x10), GDP growth (x11) and real interest rate (x12) are the most meaningful indicators. The third component is represented by public debt to GDP (x8); the fourth component is by average debt maturity (x1); and the fifth component is by central government debt to GDP (x7) (Table 3).

Table 3 Principal Components and Its Factor Loadings

Variable	**Component**					
	#1	**#2**	**#3**	**#4**	**#5**	**#6**
x1				0.919		
x2	0.953					
x3	0.712	0.555				
x4	0.565					0.603
x5	0.97					
x6	-0.904					
x7					0.926	
x8			-0.93			
x9		0.759	-0.567			
x10		0.914				
x11		-0.897				
x12		-0.896				
x13	0.668		0.66			
x14		0.848				
x15	0.231		0.63	0.574		

Source: author's own estimates

As some components have high factor loadings that explain most of the variance, we concluded that average debt maturity (x1), internal payment on external debt (x2), total debt service (x5), reserves to external debt (x6), central government debt to GDP (x7), public debt to GDP (x8), inflation (x10), GDP growth (x11) and real interest rate (x12) are the most meaningful indicators to predict the occurrence of the debt crisis (Table 4).

Table 4 The Most Significant Indicators Having High Predictive Power to Debt Crisis

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

Source: author's own estimates

These results confirm the findings of Manasse (2003) and Ciarlone and Trebeschi (2005). Interest payments on external debt were more than double in the year preceding the crisis and became increasingly large in the crisis year (Ciarlone and Trebeschi, 2005). The short-term external debt increased in the run-up to an entry into debt crisis and was significantly higher than in non-crisis episodes in the year before entry (Manasse, 2003; Ciarlone and Trebeschi 2005). The level of foreign reserves also changed significantly during crisis periods as opposed to tranquil times. The level of foreign reserves as a percentage of total external debt dropped significantly in the year preceding a crisis year (Ciarlone and Trebeschi, 2005). Real GDP growth also dropped below its average prior to crisis, and inflation rose significantly in the year preceding the crisis (Manasse, 2003; Ciarlone and Trebeschi 2005).

5. Results and Discussions

Table 5 shows that a separation problem occurred when we estimated the model by running a standard logistic regression. The estimated parameters were biased and separation problems occurred. A special module written in STATA was developed in order to solve the separation problem based on penalized maximum likelihood algorithm developed by Firth (1993). Table 5 shows the results of the penalized likelihood estimation to address the separation problem in order to reduce the bias and large standard error of the parameters.

Table 5 Results of Standard Logistic Regression at Various Scenarios

Data sets	Result
15 original variables	Separation occurred (x8* predicted data perfectly)
15 variables normalized	Separation occurred (x8* predicted data perfectly)
15 variables standardized	Separation occurred (x8* predicted data perfectly)
9 variables normalized (as defined in Table 4)	Separation occurred (x8* predicted data perfectly)
9 variables standardized (as defined in Table 4)	Separation occurred (x8* predicted data perfectly)
4 variables (GDP growth and inflation, money growth and real interest rate)	No separation problem, but no variable was significant at 5 per cent
2 variables (GDP growth and inflation)	GDP growth was significant at 5 per cent
PCA: 1 Component	C1 was not significant
PCA: 2 Components	C1 and C2 were not significant
PCA:3 Components	Separation occurred (C3** predicted data perfectly)
PCA: 4 Components	Separation occurred (C3** predicted data perfectly)
PCA: 5 Components	Separation occurred (C3** predicted data perfectly)

Source: author’s own estimates

Notes: *x8 is the ratio of public debt to GDP.

The result of the penalized likelihood estimation is presented in Table 6. At the 5 per cent significance level, GDP growth is a significant indicator for debt crisis. The probability of a crisis occurring increases by 63 per cent when annual GDP growth falls by 1 per cent. The four principal components that explain nearly 96 per cent of variation show that the probability of a debt crisis occurring increases by 4.2 per cent with a 1 per cent increase in the ratio of public debt relative to GDP. This confirms the findings of Reinhart and Rogoff (2010). The authors show that countries with high ratios of debt to GDP (90 per cent or above), including Indonesia in times of crisis 1998-2005, were associated with markedly lower growth outcomes. GDP growth plummeted significantly in times of crisis. The higher debt levels were also associated with significantly higher levels of inflation. During the debt crisis, Indonesia’s inflation rose significantly from less than 7 per cent a year before the crisis to as high as 58 per cent in the crisis year. In the aftermath of crisis, GDP growth and inflation then were moderated. One possible explanation is that the process of debt leveraging took place. A period of sharp reduction in external debt resulted in lower growth and a slowdown of the economy in the medium term (Reinhart and Rogoff, 2010).

Table 6 Firth Regression Estimates

Data sets	Wald stat	P > Chi-square	Odds ratio	Remarks
15 original variables	9.32	0.86	-	No variable was significant
15 variables normalized	9.32	0.86	-	No variable was significant
15 variables standardized	9.32	0.86	-	No variable was significant
9 variables normalized (as defined in Table 4)	7.82	0.65	-	No variable was significant
9 variables standardized (as defined in Table 4)	7.82	0.65	-	No variable was significant
4 variables (GDP growth and inflation, money growth and real interest rate)	3.11	0.54	-	No variable was significant
2 variables (GDP growth and inflation)	3.74	0.15	0.63 (GDP growth)	GDP growth was significant at 5 per cent
PCA: 1 Component	0.41	0.52	-	C1was not significant
PCA: 2 Components	2.37	0.31	-	C1 and C2 were not significant
PCA: 3 Components	5.78	0.12	0.78 (C3)	C3 was significant
PCA: 4 Components	6.73	0.15	0.80 (C3)	C3 was significant
PCA: 5 Components	6.40	0.27	0.81 (c3)	C3 was significant

Source: author’s own estimates

6. Conclusion

In this study, we applied Firth’s penalized logistic regression to examine Indonesia’s external debt crisis. The penalized regression method could be effectively used to solve a separation problem that can frequently occur in small data sets. Our results for a standard logistic regression show that a separation problem occurs where one or more variables could perfectly predict a debt crisis. The penalized regression results show that GDP growth and public debt to GDP ratio are among the most significant indicators to predict a debt crisis.

The probability of a debt crisis occurring increases by 63 per cent with a 1 per cent decrease in annual GDP growth, while an increase in the public debt to GDP ratio of 1 per cent will increase the probability of a debt crisis occurring by around 80 per cent. These confirm the findings of Reinhart and Rogoff (2010) that in emerging market economies, a high level of debt is associated with lower growth outcomes and a significantly higher level of inflation.

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