SENIOR RESEARCH

Topic: Predicting Debt Crises: A Case Study of Thailand

Name: Nicha Srimaneerungroj

ID: 5345852529

Advisor: Ajarn Somprawin Manprasert, Ph.D

Date: 9 December 2013

Senior Research Submitted in Partial Fulfillment of the Requirements

For the Bachelor of Arts degree in Economics (International Program)

The Bachelor of Arts Program in Economics

Faculty of Economics

Academic year 2013

Approve

……..

(Assoc. Prof.Sothitorn Mallikamas, Ph.D)

Chairman

Date of Approval ……

Contents Page

I. Introduction

Over the past few years we've seen our fair share of debt crises, whether it be the extremely well known Eurozone debt crisis, or the less well known Argentina debt crisis. Having seen the term "sovereign debt crisis" in the headlines so often in the past few years has led me to wonder about the worrisome future of my own country, Thailand. We saw Greece crumble from explosive levels of debt, threatening to pull the Eurozone down along with it. Thailand's debt level has been forever rising and the country's headlines concerning different populist policies paint a very scary picture for the next few years to come. Questions that started coming to my mind are "How much time do we have until a debt crisis hits our country?" and "What level of debt will finally act as a catalyst, bringing our country into a debt crisis?" Words that seem to link to Greece's overwhelming debt level seem to be populist policies and low interest rates. One out of the two seem to appear in headlines all too often for Thailand, populist policies. Are we walking in Greece's footsteps, following them straight into a debt crisis?

If we were able to predict the future, we may be able to change it and potentially even prevent something disastrous like a debt crisis from occurring. Without fully-backed/highly possible scenarios of a debt crisis occurring, Thailand's debt crisis is inevitable. The government's current spending and spending projected into the future is highly troubling. The debt level is highly correlated with government spending and it seems the government suffers greatly from myopia. An alarm must be rung to wake the government up to the reality and possibility of a debt crisis within the country. If we can somehow predict the occurrence of a debt crisis, it may act as a wake-up call for a country which seems as if it is blind to the ever growing debt burden which threatens to crush this country in its wake.

In hope of creating awareness and instilling into the country a sense of urgency surrounding the debt crisis, this paper attempts to predict whether or not a debt crisis will occur in the upcoming year. It also seeks to look past the one year mark into the distant future, however, the ability to predict falls as the time between prediction and reality increases due to the numerous uncertainties that cannot be controlled for. In order to overcome this low predictive power into the far future, another possible way to help predict the occurrence of a debt crisis is to compute a threshold at which a crisis is highly likely to occur. If we can come up with at least a rough estimate of the "danger zone," the sense of urgency may be created as people start realizing the country's proximity to the danger zone.

Even if the predictions of a mere model may not be powerful enough to prevent a debt crisis altogether, it will at least stir up some discussions and debate on the issue, which may be able to potentially moderate the outcomes to a certain extent. If we know something is coming, at least we will be able to prepare plans to handle the situation. Some may believe, whereas others may not. What we're aiming at is not for every single person to believe that a debt crisis is highly possible within the near future. It's just a heads up for the people who are willing to listen and consider the actual possibility without immediately brushing it off as nonsense.

There will be two main parts to this paper. Part I will comprise of the development of a model which will aid us in the prediction of a crisis in developing countries in general. Part II will be an application of the model created in Part I to Thailand and will be a case study. Section II will cover the research objectives of this paper. This will be followed with Section III which will lay out the initial hypothesis. Section IV gives the scope of this study, while section V is a review of the existing literature within the field of debt crisis prediction. After we get a clearer understanding of the literature within this field, we will be able to come up

with models and frameworks to simplify the mechanics going on behind the scenes in order to make the concept of debt crises occurrence easier to understand, which will be the objective of section VI. Section VII will provide details concerning the data source as well as the methods and procedures involved in the formation of a model to aid us in debt crises prediction. The results from our models developed in section VII will be discussed in section VIII. Following the results discussion, section IX will mark the beginning of Part II of the paper where the best model from part I will be applied to Thailand. In order to wrap up the study, section X will present the problems and limitations of this study and will followed up by possible extensions in the final section, section XI.

II. Research Objectives

This paper aims to create a logit early warning system (EWS) in an attempt to prevent or moderate the impact of debt crises which may potentially occur in the future years to come. After a logit model has been created, the model will be put to use in a Thailand case study, and will be used to predict whether or not a crisis will occur in the following year, based on forecasted data within the data set. Thirdly, this paper will attempt to come up with a threshold or scenario in which a debt crisis is likely or highly possible to occur. In other words, this paper seeks to shed light on the future of Thailand in terms of a debt crisis that may occur in the near future.

III. Hypothesis

There are several hypotheses that will be tested out in this study.

H1: Macroeconomic conditions play a significant role in the occurrence of a debt crisis.

H2: Thailand has not yet reached the brink of a debt crisis and will not yet face a crisis in 2014.

IV. Scope

In order to come up with a robust model that is representative of a developing country like Thailand, I decided to use data on 40 different countries, which have all been classified by Moody's as "developing" countries. Although this may seem like we are losing out on the value of the data on developed countries, after thinking through the situation, more data doesn't actually point towards a better model in all cases. In this case, our number one objective is to apply the model to the case of Thailand. If we included data on advanced countries within the model, it wouldn't fit Thailand as well, due to the fact that developed and developing countries differ to quite an extent in terms of key characteristics as well as debt crisis occurring scenarios. With this in mind, the data available was scoped down to developing countries only. This paper doesn't want to come up with a generalized list of indicators of sovereign debt crises. It seeks to apply the model to Thailand in particular, therefore after a model for developing countries has been developed, we will then scope our study down even further to a study purely on Thailand.

V. Literature Review

Due to the extensive nature of the literature and the time constraints, only a handful of papers were selected to be included within this review of the existing literature. The selection process and criteria used in this research paper are as follows. First, a Google and Google Scholar search was done on the following keywords: "debt crisis", "crisis prediction", "preventing debt crises" and "developing countries". After a primary search was done, more specific terms such as "early warning system" and "sovereign default" was added to refine

the search. Secondly, the numerous papers were screened for relevance to the research topic which is "How can we predict debt crises?" In order to prevent biases in material selection, search results on at least pages one through five were considered. After arriving at quite a large selection, the material was then reduced further. By reading the abstract and skimming the contents of each paper the number of relevant papers fell drastically relative to the search results and a majority of the search results was able to be discarded. Papers that concerned debt crises predictions directly were preferred; however, ones that concerned relationships between debt crises and a particular variable were retained as well. Lastly, the chosen papers were carefully read, analyzed and sometimes discarded from the pile due to irrelevance to the topic area. The steps listed out have culminated in this final product, the literature review.

Although there are two main types of literature concerning debt crises, namely theoretical and empirical literature, a majority of literature actually falls in the latter category. Since the objective of this paper is empirical-oriented, we will focus our attention mostly on empirical literature within the field.

Much of the empirical literature surrounding the subject of debt crises are similar in the way that they start out. It is quite common for these papers to start off with an establishment of the definition of a debt crisis. All in all, there is no agreement on a single correct definition of debt crises, with different papers defining the term differently. Fernandez et al. (2012) used a sovereign default to define debt crises. If a country is unable to pay off its interest or principal obligations, then it would be considered as being in a debt crisis (Fernandez, 2012). In addition to the more common definition of debt crises as the one used by Fernandez et al. (2012), Manasse, Roubini, and Schimmelpfennig (2003) presents a new angle to the definition by including cases of large IMF loans which exceed 100% of the country's quota as another case of a debt crisis, even though the actual crisis itself may have been avoided through the IMF's financing. In defining debt crises for the purpose of this paper, we will use a combined definition of the two most prominent definitions which includes excessive imf lendings and default ratings which is classified by S&P.

The methodology used by different papers to predict debt crises also varies greatly, with the logit model being the most commonly used method. More mathematically complex models such as the artificial neural network (ANN) which imitates the brain's processes is also one method in predicting debt crises; however, the particular method exceeds the scope of this paper in terms of its complexity and time needed to develop such a model. Probit models as seen in Nehru (2004) are also an option, however it has become less popular due to the distribution it uses in calculating probability of different events. While the logit model uses the logisitic distribution, the probit model uses the normal distribution. Since debt crises are not normal, so to speak, using the normal distribution to calculate the probability that a crisis will occur doesn't seem to make much sense. Therefore, this paper will use a logit model to aid in the prediction of debt crises into the future.

Drawing from an extensive literature review done by Jedidi (2013), the most relevant variables, which act as indicators of a debt crisis differ across different studies. However, there does seem to be a repetition of the following factors: total debt/gdp, external debt/gdp, gdp growth, trade openness, current account balance, foreign direct investment (FDI), as well as gdp per capita. This paper will follow Manasse, Roubini, and Schimmelpfennig (2003) as well as Sperber (2008) in the grouping of variables which will enable us to better analyze the outcomes from the model.

Table 1. List of variables by category

Variables by Category
External Debt variables
External Debt (US$ Bil.)
Short-term External Debt/Total External Debt
External Debt/GDP
External Debt/CA Receipts (7)
Interest Paid on External Debt (US$ Bil.)
Amortization Paid on External Debt (US$ Bil.)
total External Debt/Official Forex Reserves
Debt Service Ratio (9)
External Vulnerability Indicator (10)
Liquidity Ratio (11)
Public Debt variables
Gen. Gov. Debt (US$ Bil.) (6)
Gen. Gov. Debt/GDP (6)
Gen.Gov. Debt/Gen. Gov. Revenue (6)
Gen. Gov. Int. Pymt/Gen. Gov. Revenue (6)
Gen. Gov. FC & FC-indexed Debt/GG Debt (6)
Domestic Credit (% change Dec/Dec)
Domestic Credit/GDP
IMF's EWS variables
Current Account Balance (US$ Bil.)
Current Account Balance/GDP
Official Forex Reserves (US$ Bil.)
M2/ Official Forex Reserves (X)
Macroeconomic variables
Nominal GDP (US$ Bil.)
GDP per capita (US$)
Nominal GDP (% change, local currency)
Real GDP (% change)
Inflation (CPI, % change Dec/Dec) (1)
Gross Investment/GDP
Gross Domestic Saving/GDP
Nominal Exports of G&S (% change, US$ basis) (2)
Nominal Imports of G&S (% change, US$ basis) (2)
Openness of the Economy (3)
Net Foreign Direct Investment/GDP
Net Foreign Assets of Domestic Banks (US$ Bil.)
M2 (% change Dec/Dec)
Total Liabilities due BIS Banks/Total Assets Held in BIS Banks
Fiscal variables
Gen. Gov. Revenue/GDP (5)
Gen. Gov. Expenditures/GDP (5)
Gen. Gov. Financial Balance/GDP (6)
Gen. Gov. Primary Balance/GDP

This paper attempts to, first do a similar study of developing countries in general and secondly, to apply this model to Thailand. The end result of this paper will be a prediction of whether or not a debt crisis will occur in Thailand in the year 2014, using an up to date and comprehensive data source compiled by Moody's. Another target this paper is aiming at is the computation of a threshold for certain variables in which a debt crisis is extremely likely to occur. Although this paper is aimed at studying Thailand and its potential of going into debt crises, we will not be covering specific policies that will prevent debt crises from occurring. It would be an interesting area to probe further, using the results of this paper as a map or compass to guide the way in terms of which variable we should

VI. Conceptual Framework

To be able to clearly picture the dynamics involved in the occurrence of a debt crisis, I have come up with the following diagram.

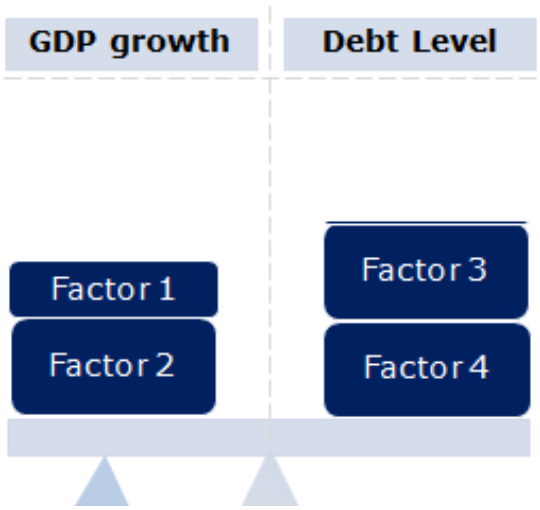

Figure 1: The seesaw of debt crises

Let's start out with the big picture. There are basically two sides involved in a debt crisis. The first more obvious side is the debt level aspect of the scenario. GDP and the state of economic growth is a less obvious factor that may be easy to overlook, however, overlooking growth is an unforgivable deed. If we do not consider growth in our assessment of the situation, we will miss out on half of what is actually going on. After talking to a senior economist and researcher at the Bank of Thailand, I gained a much richer insight into what actually drives a debt crisis and am now more able to look at the issue more holistically. The gist of the conversation can be summarized by the following quote: "Debt in and of itself isn't a problem…the problem arises when the economy starts having problems." The seesaw diagram above is quite simple and easy to understand. On the left hand side, we have GDP growth, which can basically be taken as a representation of the state of the economy in general. The weights on the GDP growth side are the multifarious factors that affect GDP growth. There are definitely more than 2 factors that affect GDP growth, and I'd like to point out that the 2 factors are just for illustration's sake. The same goes for factors 3 and 4 on the debt side of the scenario. If we look closely, we will see that each factor is different in terms of size. This is to signify that some factors may have a greater impact on GDP growth or debt level than others. When the two sides are balanced there will be no risk of a debt crisis, however, if more and more weight starts piling onto the debt side relative to the gdp growth side, the seesaw will be in greater risk of tipping over. Within the model, a tipping over of the seesaw will represent an occurrence of a debt crisis. After hearing this, many may start arguing that what if we have lots of weight piled onto the growth side? How can high growth cause a debt crisis? To answer this question, we must return to the diagram. We have a small triangle supporting the gdp growth side and no matter the amount of weight piled on, the seesaw will never tip over due to the gdp growth side. The greater the weight piled onto the gdp growth side, the more difficult it becomes for the seesaw to tip over onto the debt level side. Now that we understand more clearly the 2 levers behind the occurrence of a debt crisis, let us consider why an unstable economy is the root of the problem. Let's say the debt level weights slightly outweigh the gdp growth weights. This will cause the seesaw to dip slightly lower on the debt level side. The seesaw will not tip over yet, as the debt side of the situation

hasn't outweighed the growth side by that much. We can't rest assured as now, the situation is extremely fragile. The slightest addition of weight onto the debt side can mean a crash of the seesaw and an economy plunging into a debt crisis. Any other external shocks or the slightest touch by an outside source can also cause the seesaw to tip over. Now that we've considered the first "seesaw" diagram in detail, let us understand why a problematic economy can lead to a vicious debt reinforcing cycle shown in diagram 2.

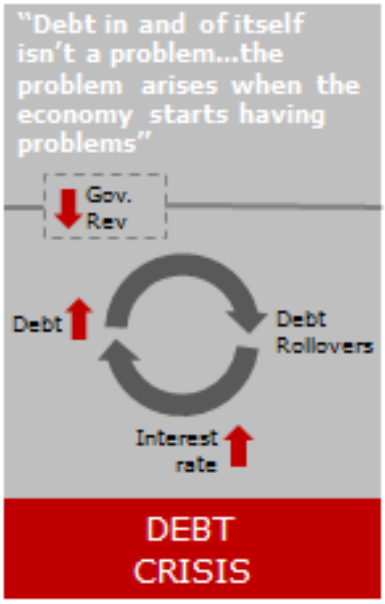

Figure 2: The vicious cycle of debt

Let us start out with a problematic state of the economy. Assuming that this will lead to a fall in government revenue, it will cause the government to be able to repay smaller amounts of the principal and interest payment, ultimately leading up to an increase or accumulation of the debt balance. The step that follows when the government is unable to fulfill its obligations is a debt rollover or a refinancing of the debt. When this occurs, investors may lose confidence in the country and request higher yields, thus causing an increase in the government's interest rate and ultimately the interest payment. Larger interest payments, if not paid will add on to the already existing debt balance. This cycle goes on and on and the worst case scenario that we've seen Greece face is a debt spiral, where the debt level spirals out of control.

These 2 diagrams, both the seesaw of debt crises and the vicious cycle of debt, will help us to more clearly understand the mechanics behind the scene as we move on to discuss the model and thresholds in greater detail.

VII. Data, Methods, and Procedures

Data

From the literature review, recall that we will be including data from 5 different categories, namely external debt, public debt, IMF's EWS, macroeconomic, and fiscal variables (Sperber 2008). The prior list exactly follows Sperber (2008) along with a rough direction from Manasse, Roubini, and Schimmelpfennig (2003). Some authors such as Jedidi relies on individually drawing the data from multiple sources such as from other published papers, WDI, WEO, IFS and GFD to name a few. Initially, this paper was going to take the same path in data collection and compiling. However, after reading Sperber (2008), I realized that we don't have to do all the data collection and compilation ourselves. Moody's statistical handbook: country credit is the singular source of data that feeds into Sperber's paper. This not only saves time needed to find data from different sources but also allows us to get rid of the worry that data sets from different data sources will cover different time periods, thus making it more difficult to run analysis. Another benefit that can be directly seen is the internal consistency of the data itself. Since all of the data is from one singular and deemed trustworthy source, we won't have to worry about inconsistencies within the data; a problem that would've arisen if we were to draw data from different sources. With this in mind, we proceed using Moody's Statistical Handbook: Country credit 2013 May as our singular data source for input into our model. Apart from Moody's Statistical Handbook, we also rely on two other sources for the creation of a "crisis" variable which is the key and extremely crucial to our study. These two additional resources are 1) Standard and Poor's Sovereign Rating and

Country T&C Assessment Histories report and 2) IMF's History of Lending Arrangements by country.

Moody's Statistical Handbook: Country Credit 2013 May

This data set compiled by Moody's is the most updated version to date containing statistics as of May 10, 2013. Moody's compiled the figures within the handbook from the following sources: IMF, OECD, World Bank, BIS, and Eurostat. National statistics as well as international sources are also drawn from for indicators which may only be available from national sources. Some variables may be missing for specific countries due to lack of availability of the data. The data set comprises of a total of 118 different countries, each with a comprehensive set of 54 variables over the years 2003-2012, along with an additional forecasted set of data for the years 2013 and 2014. The 54 variables are subdivided into 4 large groups including: economic structure and performance, government finance, external payments and debt, and monetary, external vulnerability and liquidity indicators.

Standard & Poor's Sovereign Rating and Country T&C Assessment Histories

This report contains S&P's sovereign rating and assessment histories as of Dec. 31, 2012. Within the report, the table is broken down by country, which allows us to easily determine the episodes of crises that a country has faced or is currently facing. Ratings range from AAA all the way to SD and D, which refers to "selective default" and "default," respectively. If we recall our definition of debt crises from the beginning of our study, countries which receive the SD or D rating would qualify as being in a debt crisis.

IMF's History of Lending Arrangements

The IMF lending arrangement data was obtained from the IMF website under the IMF Financial Data by Country. According to the IMF, lending arrangements are "similar to a line of credit." Data was obtained individually for each country within our sample. Recall from Manasse, Roubini, and Schimmelpfennig (2003), their definition of a debt crisis. They included within their definition, large IMF loans that exceeded the quota by 100%. We adopt their definition in the formation of our definition, therefore if data from the IMF's lending arrangements show excessively large IMF loans, the country will be considered as being in a debt crisis during that time period.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Nominal GDP (US$ Bil.)	440	402.64	911.68	8.1	9324.5
GDP per capita (US$)	440	7623.47	5922.61	544	33153
Nominal GDP (% change, local currency)	440	12.07	8.74	-29.1	58.4
Real GDP (% change)	440	4.57	3.82	-17.7	18.5
Inflation (CPI, % change Dec/Dec) (1)	440	6.06	5.12	-1.9	42.6
Gross Investment/GDP	440	23.45	6.43	11.1	49.2
Gross Domestic Saving/GDP	440	23.95	11.67	-7.6	57.2
Nominal Exports of G&S (% change, US$ basis) (2)	440	13.85	15.74	-50.5	88.7
Nominal Imports of G&S (% change, US$ basis) (2)	440	14.42	16.60	-43	54.3
Openness of the Economy (3)	440	80.89	36.34	22.1	204.7
Gen. Gov. Revenue/GDP (5)	440	26.45	9.73	11.1	53.8
Gen. Gov. Expenditures/GDP (5)	440	28.44	9.89	12	52.2
Gen. Gov. Financial Balance/GDP (6)	440	-2.00	3.51	-11.1	16.8
Gen. Gov. Primary Balance/GDP	440	0.59	3.32	-8.3	17.1
Gen. Gov. Debt (US$ Bil.) (6)	440	148.76	320.13	1.73	2714.8
Gen. Gov. Debt/GDP (6)	440	40.61	23.38	3.9	138
Gen.Gov. Debt/Gen. Gov. Revenue (6)	440	174.61	112.29	10.2	672.8
Gen. Gov. Int. Pymt/Gen. Gov. Revenue (6)	440	11.11	9.65	0	62.9
Gen. Gov. FC & FC-indexed Debt/GG Debt (6)	415	44.61	28.64	1.3	108.6
Current Account Balance (US$ Bil.)	440	4.78	41.57	-95.51	420.57
Current Account Balance/GDP	440	-0.41	6.85	-22.6	38.8
External Debt (US$ Bil.)	440	104.77	129.00	3.9	796.99
Short-term External Debt/Total External Debt	429	21.08	13.22	0	74.1
External Debt/GDP	440	44.39	27.92	8.5	189.5
External Debt/CA Receipts (7)	440	103.21	55.14	22.3	427.8
Interest Paid on External Debt (US$ Bil.)	440	3.24	4.03	0.09	25.64
Amortization Paid on External Debt (US$ Bil.)	440	12.20	17.53	0.06	163.98
Net Foreign Direct Investment/GDP	440	2.58	2.50	-3.4	14.9
Official Forex Reserves (US$ Bil.)	440	98.95	352.53	0.25	3356.36
Net Foreign Assets of Domestic Banks (US$ Bil.)	396	0.47	35.81	-101.09	300.47
M2 (% change Dec/Dec)	398	16.10	13.69	-5.5	120
Domestic Credit (% change Dec/Dec)	399	15.78	16.21	-20.7	91.3
Domestic Credit/GDP	399	56.57	29.24	10.2	155.1
M2/ Official Forex Reserves (X)	399	3.71	2.97	0.7	27.1
total External Debt/Official Forex Reserves	440	337.19	304.28	17.9	2700.3
Debt Service Ratio (9)	440	17.51	14.32	1.5	89.2
External Vulnerability Indicator (10)	440	120.28	142.27	0.7	1266.2
Liquidity Ratio (11)	400	81.10	105.75	4.4	960.7
Total Liabilities due BIS Banks/Total Assets Held in BIS Banks	400	174.58	206.43	9.1	1799.9

Methods and Procedures

Before we begin creating an econometric model, we go through some tedious steps of data formatting in order to finally arrive at an econometric modeling-compatible data set. A brief procedure follows: After we have the data, it had to be transferred from report format into spreadsheet. A series of excel macros were used in speeding up the tedious process. Once all the data had been put into excel, it then had to be formatted into stacked time series, which is the format used by most econometric modeling programs.

Now that we have transformed our data into a form that is compatible with econometric modeling programs, we then move on to the creation of our model. As was portrayed by section V, an extensive review of the literature, the models differ from paper to paper with varying degrees of complexity. For the sake of this paper, I decided to follow the Logit model which was used by Fuertes (2006), Gourinchas et Obstfeld (2011), and the IMF's working paper by Manasse, Roubini et Schimmelpfennig (2003) to name a few. Other models such as the Probit model and the artificial neural network were considered, however, the Logit model surpasses the probit model in terms of the distribution, which better fits the characteristic of debt crises. The artificial neural network shown in Fioramanti (2006) also had interesting insights to give but due to the boundaries of this paper, the complexity of this model was way too high to be completed within the allotted time and with the resources and knowledge at hand.

Logistic Regression (Logit Model)

Drawing from Sperber's easy to follow explanation; a general logistic regression can be represented by the following equation:

$$Y_{it} = \alpha_i + \beta_i X_{it-1} + u_{it}$$

$$Y_{it} = \begin{cases} 1 & Crisis \\ 0 & No\ crisis \end{cases}$$

The following equation allows us to calculate the probability of debt crises:

$$\Pr(Y = 1|X_1, X_2, \dots, X_k) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)$$

$$= \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)}}$$

F is the logistic distribution function used to determine the probability of an event occurring.

Y is the dependent variable, which in logistic regressions takes a binary value of either 1 or 0.

$X's$ are independent variables, which are believed to explain the value of Y.

$\beta's$ are parameters.

Similar to when we run an OLS regression, when we run a logistic regression we are trying to find values of β that will best fit the data. Therefore, the end result of our logistic regression will be coefficient values β_0 all the way to β_k, which represent the impact of each

independent variable X on the probability of the outcome, Y, being equal to 1. After running each model, we will decide on the best model by looking at the goodness of fit value represented by the pseudo r-squared values of each individual model, where a higher value points to a greater explanatory power. While running each model, we may have to determine whether or not the independent variables ($X's$) we included in the regression are actually significant towards impacting the dependent variable (Y).

The output of a Logit model or a logistic regression is a binary value dependent variable. This binary outcome is extremely useful in our case as the goal of our analysis is to predict whether or not a crisis will occur in the following year. Following Manaasse, Roubini et Schimmelpfennig (2003) and a more recent paper by Sperber (2008), we create 2 variables, namely a "crisis" and "year before a crisis" variable, where the second is just a lagged form of the first. In order to create the "crisis" variable, we follow the definition of debt crisis that we have decided upon after doing an extensive review of the literature. After we were able to classify the observation as experiencing or not experiencing a crisis, we then assigned a binary value to the 2 states. The numbers zero and one were assigned to the no-crisis state and crisis state, respectively. After this "crisis" variable was created, the "year before a crisis" variable followed naturally as a separate variable which lagged the "crisis" variable by one year. A similar logic follows for the value of the "year before a crisis" variable. If a country was about to face a crisis in the following year, then the value of this variable would be one; however, if this isn't the case, a value of zero would be assigned. Since our end goal is to predict whether or not a crisis will occur in the following year, the dependent variable that we will use is the "year before crisis" variable.

After we have created these two additional variables, we move on to actually running the logistic regressions. We follow the 3 methods laid out by Sperber (2008) and Manasse, Roubini, and Schimmelpfennig (2003).

Model I:

This first method involves running logistic equations that involved only 1 independent or explanatory variable (X). The dependent variable (Y) is the lagged crisis variable. By running these equations for every single one of the 39 explanatory variables, we are able to determine the individual impact of each variable on the occurrence of a debt crisis. Since we only want significant variables, we screened out variables which did not meet the 90% significance level, leaving us with 27 remaining variables. All of these 27 variables were then used as inputs in another logistic regression which now no longer comprises of 1 explanatory variable, but instead 27 of them. This equation produced a Mc-Fadden R-squared value of 0.532 where 10 out of the 27 variables met the 90% significance requirement. Although the Mc-Fadden R-squared value was acceptable, the model contained as much as 17 variables which were, in this case, insignificant. The results we obtain from this model can't be used for interpretation due to the inaccurate insights that it will provide as a result of the large number of insignificant variables. In order to arrive at a reliable model that can be interpreted trustworthily, we must get rid of the insignificant variables. Following the guidance of Manasse, Roubini, and Schimmelpfennig (2003), we do not bluntly remove all the insignificant variables at the same time. We more strategically carry out the removal of insignificant variables by removing them one at a time, in a specific order which involved removing the least significant variable first. After this was done, a re-evaluation of the model would be done to pin-point the next least significant variable which would then be removed. Repeating this process over and over, we finally arrive at a single equation in which all explanatory variables meet the 90% significance requirement. The final equation comprises of 24 explanatory variables and a Mc-Fadden R-squared value of 0.62.

Model II:

Our second model uses the best-in-group selection method. In order to come up with our finalized model II, we first start off with our 5 different variable categories (see table #) including external debt, public debt, IMF's EWS, macroeconomic, and fiscal variables. We then run a logistic regression for each category, for example, our fiscal variable logistic regression would contain the following explanatory variables: general government revenue/GDP, general government expenditures/GDP, general government financial balance/GDP, and lastly general government primary balance/GDP. After running this regression, we repeat the elimination of the least significant variables that do not meet the 90% significance criteria. This step is repeated until all independent variables are significant at the 10% level. Afterwards, the remaining variables are set aside as we continue repeating this best-in-group selection process for the remaining variable categories. When all 5 categories have undergone the best-in-group selection and have yielded their most predictive and relevant variables, we combine the representatives from each variable category into one large logistic regression, which specifically in this case comprises of 20 variables in all. This can be further broken down by category, yielding the following results: 3 external debt variables, 2 public debt variables, 1 IMF's EWS variable, 10 macroeconomic variables, and finally 3 fiscal variables. From this alone, an intermediate insight that we can draw from this is that macroeconomic factors do have quite an important role to play. However, we must wait until the final logistic regression is derived to be able to fully state and back up this claim. The 20-variable logistic regression was run and the same elimination process took place and finally yielded an equation of 11 variables, comprising of 9 and 2, macroeconomic and external debt variables, respectively. It seems that the insight we gained earlier, that macroeconomic variables play a big role in crisis prediction is indeed correctly drawn, as is backed up by this final logistic regression: Model II. Model II's McFadden R-squared value improved from 0.436 before variable elimination to 0.447 afterwards, which is comparable to but slightly lower than model I's value of 0.488.

Model III:

The final method is to throw in all of the variables into one extremely large logistic regression. The first step to achieve this model is exactly the same as model I. The difference is in the strategy we use to remove insignificant variables that do not meet our required 90% significance. Recall from model I that the first elimination step we took was to remove all variables that did not meet the 90% significance criteria; this lead to the removal of 12 variables all at once. In this third and final model, instead of removing all 12 at once, we take a very meticulous approach in the elimination of variables. One by one we remove the insignificant variables until every single variable achieves our desired level of significance. Mirroring the tedious process and careful approach of eliminating variables, we come to a final logistic regression which comprises of 24 variables and an all-time high McFadden R-squared value of 0.62 (see Table #). Breaking down the model further, we find out that the 24 variables comprise of 11 macroeconomic variables, 5 external debt variables, 4 public debt variables, and 3 fiscal variables. This seems to point towards the same conclusion that was drawn earlier after obtaining the results of model II. Macroeconomic variables do seem to play a big role in debt crises prediction; however, one thing that we've forgotten to take into consideration is the fact that at the very beginning, our variable pool was dominated by macroeconomic variables. Therefore, we must still take caution when interpreting the composition of these models and in drawing insights and conclusions from them.

VIII. Results

Model III turns out to be the best model from the three models that were run within this study, with a Mc-Fadden R-squared value of 0.622. Its predictive power is quite high, predicting crises correctly 93.1% of the time for the data set used. When calculating the predictive power of a particular model, we must consider the number of times the model correctly predicts a crisis when there is one and predicts no crisis when there is none. These accurate predictions are called "hits." If the model predicts a crisis when there is none, or vice versa, we call these scenarios a "false alarm" and a "miss," respectively. The best model will be one that yields the highest number of "hits" relative to the number of "misses" and "false alarms." As is shown in Appendix III, Model III produced 350 "hits," 8 "false alarms", and 18 "misses." "False alarms" and "misses" can be more formally referred to as a type I error and a type II error, respectively.

Table 3. Regression Results

	Model I			Model II			Model III		
	Pseudo R^2= 0.488			Pseudo R^2= 0.447			Pseudo R^2= 0.622		
	Logit Coeff	P-value		Logit Coeff	P-value		Logit Coeff	P-value	
	-1.75322	0.20838		-1.32822	0.19954		5.77649	0.05991	*
External Debt (US$ Bil.)									
Nominal GDP (US$ Bil.)	-0.0242009	0.00034	***	-0.0035511	0.02877	**	-0.0290129	0.00002	***
GDP per capita (US$)							-0.000191582	0.00885	***
Nominal GDP (% change, local currency)	0.231755	<0.00001	***	0.171719	<0.00001	***	0.447067	<0.00001	***
Real GDP (% change)				-0.154358	0.02993	**	-0.297313	0.01689	**
Inflation (CPI, % change Dec/Dec) (1)									
Gross Investment/GDP	-0.135781	0.03063	**	-0.118753	0.01359	**	-0.244904	0.00737	***
Gross Domestic Saving/GDP				-0.0663511	0.00025	***			
Nominal Exports of G&S (% change, US$ basis) (2)	-0.0656844	0.00005	***	-0.0448285	0.00354	***	-0.109952	0.00761	***
Nominal Imports of G&S (% change, US$ basis) (2)				0.0293345	0.08856	*	0.0632744	0.05427	*
Openness of the Economy (3)	-0.0526776	0.00005	***				-0.0642478	0.00023	***
Gen. Gov. Revenue/GDP (5)							-1.90422	0.00289	***
Gen. Gov. Expenditures/GDP (5)							1.64774	0.00362	***
Gen. Gov. Financial Balance/GDP (6)									
Gen. Gov. Primary Balance/GDP							1.35493	0.00468	***
Gen. Gov. Debt (US$ Bil.) (6)	0.0307721	0.00021	***				0.0235003	0.00078	***
Gen. Gov. Debt/GDP (6)									
Gen.Gov. Debt/Gen. Gov. Revenue (6)									
Gen. Gov. Int. Pymt/Gen. Gov. Revenue (6)							-0.38091	0.00592	***
Gen. Gov. FC & FC-indexed Debt/GG Debt (6)	0.0509942	<0.00001	***				0.0300572	0.06344	*
Current Account Balance (US$ Bil.)	-0.10191	0.00401	***				-0.150535	0.00051	***
Current Account Balance/GDP									
Short-term External Debt/Total External Debt									
External Debt/GDP							0.036796	0.00339	***
External Debt/CA Receipts (7)				0.023357	<0.00001	***			
Interest Paid on External Debt (US$ Bil.)	1.0886	0.00012	***				1.53767	<0.00001	***
Amortization Paid on External Debt (US$ Bil.)							-0.161118	0.00068	***
Net Foreign Direct Investment/GDP				-0.165844	0.07329	*	-0.241037	0.07664	*
Official Forex Reserves (US$ Bil.)	-0.0920796	0.00515	***						
Net Foreign Assets of Domestic Banks (US$ Bil.)				-0.0528745	0.00889	***			
M2 (% change Dec/Dec)									
Domestic Credit (% change Dec/Dec)									
Domestic Credit/GDP	0.0690875	0.00048	***				0.0764736	0.00521	***
M2/ Official Forex Reserves (X)	-0.442172	0.0006	***				-0.472872	0.01091	**
total External Debt/Official Forex Reserves									
Debt Service Ratio (9)									
External Vulnerability Indicator (10)							0.00515556	0.018	**
Liquidity Ratio (11)	-0.0213438	0.00066	***	-0.006515	0.02906	**	-0.0374023	0.00373	***
Total Liabilities due BIS Banks/Total Assets Held in BIS Banks	0.00864584	0.0003	***				0.01348	0.00305	***

IX. Thailand Case Study

A. Forecasted Data

After obtaining the generalized logistic regression model which applies specifically to developing countries, we then put this model to use in predicting debt crises in Thailand. After inputting Moody's forecasted data for 2013 and 2014 into the generalized model, we obtain the following results. In both 2013 and 2014, the model yields the result: "No Crisis." Although this may be reassuring for some, this does not mean that we are safe. When looking at the possibility of debt crises occurring, we should look much further into the future than just one single year.

B. Thresholds and interesting variables

Looking further into the future, we attempt to calculate thresholds for individual variables in which, all else held constant, the country will go into a debt crisis. Since model III is our best model, we will be using model III as our base case. The following variables were selected from model's III pool of variables to be taken a closer look at: external debt to GDP, current account balance, general government debt, as well as interest paid on external debt.

External debt to GDP: All else held constant, external debt to GDP must reach a value of 1680.84 for our model to predict a debt crisis. The current external debt to GDP is equal to 32.2; therefore we see that it is highly unlikely that a debt crisis will occur in 2014 due to higher external debt to GDP within the near future.

Current account balance: All else held constant, the current account balance must be equal to -306.7 billion USD in order for our model to predict a debt crisis, in other words, Thailand must run an account deficit of roughly 306 billion USD for a crisis to occur due to this particular variable. The current account balance is currently at a surplus of 6.11 billion USD. Similar to the case of external debt to GDP, it seems unlikely that a fall in the current account balance will precipitate a debt crisis next year.

General government debt: All else held constant, the general government debt must reach 1.89 trillion USD for our model to predict a debt crisis for the year 2014. The current level of general government debt is predicted to be 137.29 billion USD, which again seems quite far away from the threshold value.

Interest paid on external debt: All else held constant, the interest paid on external debt will cause the model to predict a crisis if the value reaches 39.9 billion USD. The current interest paid on external debt is 1.5 billion USD.

X. Problems and Limitations

The limitation that likely has the greatest impact on the study is the data limitation. The data set used covers the years 2003-2012; however this data doesn't cover many of the important debt crises that have occurred in the past. Therefore, the predictive power of the model may have been lowered due to the slightly incomplete nature of the data set.

Another limitation is the accuracy of the Moody's forecasted data for the years 2013 and 2014 which are missing several variables and may not be that accurate, as is the nature of forecasts. Although there is nothing within our power to fix the second issue of the accuracy of the forecasts and its inherent nature for being inaccurate, we can however try to obtain a larger data set from the same source in order to increase the comprehensiveness of the data set.

XI. Possible Extensions of the Study

Extensions that can be made on this study are endless; however, here are some ideas of potential areas that can be extended on. The first and simplest extension involves the usage of a more extensive data set as input into the creation of the logit model. The current data set is Moody's Statistical Handbook: Country Credit May 2013, which covers the years 2003-2012 and provides a forecast of 2013 and 2014. Since this data set covers only the past decade, it is unable to capture crises that have occurred before 2002. Optimal data sets to augment the existing data set with are older versions of Moody's Statistical Handbook: Country Credit. If older versions can be found and pieced together into an extremely long time series, it is highly likely that the predictive power of the model will increase by a significant extent. As a result, we will see more accurate prediction of the occurrence of debt crises.

Secondly, an in-depth study of the government's current policies can be done in order to provide policy recommendations alongside results from this study which shows the key variables that act as crises indicators.

Thirdly, more insights into the potential occurrence of debt crises in Thailand can be captured if create a tree EWS which uses Classification and Regression Tree (CART) as is seen in Manasse, Roubini, Schimmelpfennig et. (2003). Manasse, Roubini, and Schimmelpfennig (2003) shows that this method aids in capturing more complex relationships such as nonlinear interactions within a large pool of explanatory variables.

Lastly, a more qualitative study on the possibility of a debt crisis occurring in our country can also be done by performing a detailed analysis of the country's balance sheet. Findings from this research may be able to back up or refute the conclusions found within this paper. If the findings match, then it will serve as weight on the results of this paper's findings, thus achieving our goal of raising awareness and creating a sense of urgency in dealing with the possibility of a debt crisis in the near future.

Appendix I

Model 1

Model 5: Logit, using 376 observations
Dependent variable: Year_before_cri
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1.75322	1.39363	-1.2580	0.20838	
Nominal_GDP__US	-0.0242009	0.00675533	-3.5825	0.00034	***
Nominal_GDP___	0.231755	0.0471646	4.9138	<0.00001	***
Gross_Investmen	-0.135781	0.0628083	-2.1618	0.03063	**
Nominal_Exports	-0.0656844	0.0162588	-4.0399	0.00005	***
Openness_of_the	-0.0526776	0.0129252	-4.0756	0.00005	***
Gen__Gov__Debt_	0.0307721	0.00830066	3.7072	0.00021	***
Gen__Gov__FC__	0.0509942	0.0109048	4.6763	<0.00001	***
Current_Account	-0.10191	0.0354134	-2.8777	0.00401	***
Interest_Paid_o	1.0886	0.28377	3.8362	0.00012	***
Official_Forex_	-0.0920796	0.0329152	-2.7975	0.00515	***
Domestia	0.0690875	0.0197905	3.4909	0.00048	***
M2__Official_Fo	-0.442172	0.128783	-3.4335	0.00060	***
Liquidity_Ratio	-0.0213438	0.00626898	-3.4047	0.00066	***
Total_Liabiliti	0.00864584	0.00239255	3.6137	0.00030	***

Mean dependent var	0.130319	S.D. dependent var	0.337103
McFadden R-squared	0.487914	Adjusted R-squared	0.384828
Log-likelihood	-74.51327	Akaike criterion	179.0265
Schwarz criterion	237.9704	Hannan-Quinn	202.4252

Number of cases 'correctly predicted' = 342 (91.0%)
f(beta'x) at mean of independent vars = 0.337
Likelihood ratio test: Chi-square(14) = 141.992 [0.0000]

Appendix II

Model 2

Model 40: Logit, using 396 observations
Dependent variable: Year_before_cri
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1.32822	1.03536	-1.2829	0.19954	
External_Debt_C	0.023357	0.00433282	5.3907	<0.00001	***
Liquidity_Ratio	-0.00651497	0.00298479	-2.1827	0.02906	**
Nominal_GDP__US	-0.00355108	0.00162402	-2.1866	0.02877	**
Nominal_GDP___	0.171719	0.026584	6.4595	<0.00001	***
Real_GDP____cha	-0.154358	0.0710996	-2.1710	0.02993	**
Gross_Investmen	-0.118753	0.048118	-2.4680	0.01359	**
Gross_Domestic_	-0.0663511	0.0181383	-3.6581	0.00025	***
Nominal_Exports	-0.0448285	0.0153685	-2.9169	0.00354	***
Nominal_Imports	0.0293345	0.0172245	1.7031	0.08856	*
Net_Foreign_Dir	-0.165844	0.0925964	-1.7910	0.07329	*
Net_Foreign_Ass	-0.0528745	0.0202087	-2.6164	0.00889	***

Mean dependent var	0.128788	S.D. dependent var	0.335389
McFadden R-squared	0.446547	Adjusted R-squared	0.367648
Log-likelihood	-84.17694	Akaike criterion	192.3539
Schwarz criterion	240.1308	Hannan-Quinn	211.2816

Number of cases 'correctly predicted' = 365 (92.2%)
f(beta'x) at mean of independent vars = 0.335
Likelihood ratio test: Chi-square(11) = 135.834 [0.0000]

Appendix III

Model 3

Model 18: Logit, using 376 observations
Dependent variable: Year_before_cri
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	5.77649	3.07019	1.8815	0.05991	*
Nominal_GDP__US	-0.0290129	0.00677299	-4.2836	0.00002	***
GDP_per_capita_	-0.000191582	7.31819e-05	-2.6179	0.00885	***
Nominal_GDP___	0.447067	0.0977712	4.5726	<0.00001	***
Real_GDP____cha	-0.297313	0.124448	-2.3891	0.01689	**
Gross_Investmen	-0.244904	0.0913946	-2.6796	0.00737	***
Nominal_Exports	-0.109952	0.0411966	-2.6690	0.00761	***
Nominal_Imports	0.0632744	0.0328757	1.9247	0.05427	*
Openness_of_the	-0.0642478	0.017446	-3.6827	0.00023	***
Gen__Gov__Revenn	-1.90422	0.639213	-2.9790	0.00289	***
Gen__Gov__Expen	1.64774	0.566293	2.9097	0.00362	***
Gen__Gov__Prima	1.35493	0.479051	2.8284	0.00468	***
Gen__Gov__Debt_	0.0235003	0.00699383	3.3602	0.00078	***
Gen__Gov__Int__	-0.38091	0.138408	-2.7521	0.00592	***
Gen__Gov__FC__	0.0300572	0.0161935	1.8561	0.06344	*
Current_Account	-0.150535	0.0433402	-3.4733	0.00051	***
External_Debt_G	0.036796	0.0125592	2.9298	0.00339	***
Interest_Paid_o	1.53767	0.331069	4.6446	<0.00001	***
Amortization_Pa	-0.161118	0.0474337	-3.3967	0.00068	***
Net_Foreign_Dir	-0.241037	0.136139	-1.7705	0.07664	*
Domestia	0.0764736	0.0273723	2.7938	0.00521	***
M2__Official_Fo	-0.472872	0.185765	-2.5455	0.01091	**
External_Vulner	0.00515556	0.00217945	2.3655	0.01800	**
Liquidity_Ratio	-0.0374023	0.0128976	-2.8999	0.00373	***
Total_Liabiliti	0.01348	0.00455058	2.9623	0.00305	***

Mean dependent var	0.130319	S.D. dependent var	0.337103
McFadden R-squared	0.621694	Adjusted R-squared	0.449883
Log-likelihood	-55.04710	Akaike criterion	160.0942
Schwarz criterion	258.3339	Hannan-Quinn	199.0920

Number of cases 'correctly predicted' = 350 (93.1%)
f(beta'x) at mean of independent vars = 0.337
Likelihood ratio test: Chi-square(24) = 180.924 [0.0000]

Appendix IV

List of Developing Countries			
Argentina	El Salvador	Lithuania	Romania
Bolivia	Guatemala	Malaysia	Russia
Brazil	Hungary	Mexico	South Africa
Chile	India	Morocco	Thailand
China	Indonesia	Oman	Trinidad and Tobogo
Colombia	Israel	Pakistan	Tunisia
Costa Rica	Jamaica	Panama	Turkey
Czech Rep.	Kazakhstan	Peru	Ukraine
Dominican Rep.	Korea	Philippines	Uruguay
Ecuador	Latvia	Poland	Venezuela

Source: Moody's Statistical Handbook: Country Credit May 2013; all of these countries have been classified by Moody's as developing countries and total to 40 countries

Reference List

Fernandez, L., Erce, A. and Irina Balteanu. 2012. Bank Crises and Sovereign Defaults: Exploring the Links.

Fioramanti, M., 2006. Predicting Sovereign Debt Crises Using Artificial Neural Networks: a Comparative Approach. ISAE Working Paper n.72.

Fuertes, A., and Elena Kalotychou, 2006. Early Warning Systems for Sovereign Debt Crisis: The Role of Heterogeneity. Elsevier Journal of Computational Statistics & Data Analysis volume 51, issue 2. 1420-1441.

Gourinches, P.O and Maurice, Obstfeld, 2011. Stories of the Twentieth Century for The Twenty First, National Bureau of Economic Research (NBER), Working Paper 17252.

Jedidi, Ons, 2013. Predicting Sovereign Debt Crises: A Panel Data Approach Using Composit Indices. University of Rennes.

Manasse, Paolo, Nouriel Roubini, and Axel Schimmelpfennig. Predicting Sovereign Debt Crises, IMF Working Paper 03/22, 2003.

Kraay, A., and V. Nehru, 2004. When is External Debt Sustainable?, The World Bank Policy Research Working Paper 3200.

Peter, M., 2002. Estimating Default Probabilities of Emerging Market Sovereigns: A New Look at a Not-so-new Literature. HEI Working Paper No: 06/2002.

Sperber, Matthew. 2008. Predicting Financial Debt Crises: A Case Study of India. Duke University.