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Early Warning System for Government Debt Crisis in Developing Countries[1]

Abstract: This study develops an early warning signal (EWS) of government debt crisis using a panel data consisting of 43 developing countries over the period of 1960 to 2017. It employs two different methods: the noise to signal ratio to capture the signaling power of individual indicators; and the binomial logistic regression to construct a more general model. The binomial logistic regression offers a better predictive power relative to the noise to signal ratio. The binomial logistic regression can predict 61.5% of the government debt crisis 2 years in advance. An increase in inflation, government and private debt exposures, external debt to exports, ratio of short-term external debt to foreign exchange reserves, and the ratio of external interest payments to gross national income can signal an upcoming debt crisis. Similarly, a continuous decline in the gross domestic product (GDP) and government consumption also increase the likelihood of government debt crisis.

Keywords: Government debt crisis; Systemic risk; Macroprudential; sovereign debt crisis.

JEL Classification: H63; H68.

[1] All opinions stated in this paper do not represent Bank Indonesia policies or stances. The authors are responsible for technical and non-technical errors in this paper. The authors would like to thank Cicilia A. Harun, Deputy Director of the Macroprudential Policy Department for the advice given in writing this paper.

1. Introduction

This paper develops an EWS of government debt crisis for developing countries. Studies define government debt crisis in different ways.[2] For instance, Cerovic, Gerling, Hodge, and Medas (2018) define debt crisis as a condition in which government faces a distress in their balance sheet, resulting from imbalances in inflow and outflow. Daniel and Shiamptanis (2018) contend that debt crisis refers as the period in which the government debt repayment requires larger current and expected future values for the primary surplus. However, the Standard & Poor's (S&P's) definition is the most commonly used (Balteanu and Erce, 2014; Gennaioli, Martin, and Rossi, 2014). S&P's defines government debt crisis as a situation whereby: (i) the government does not meet scheduled debt service on the due date or (ii) creditors are offered either a rescheduling (bank debt) or a debt exchange (bond debt) in less favorable terms than the original issue.

In an uncertain world, there is a need to develop indicators or signals of bad and good economic times (see Juhro and Iyke, 2019). The Greek debt crisis in 2010, in particular, reminds the world that the suddenness of the government debt crisis poses a potential risk to an economy. As a result, a growing number of studies attempt to identify a set of indicators, which can act as an early warning instrument for government debt crisis. The establishment of an Early Warning System is very important as it can hinder a continuous deterioration that can affect the financial system stability (Abubakar, Astuti, and Oktapiani, 2018; Padhan, and Prabheesh, 2019). However, the number of studies concerning early warning signal for debt crisis is not as numerous as studies on currency and banking crisis. A large share of these studies also either concentrates on developed economies, where data are readily available at higher frequencies, or make no separation between developed and emerging economies (Fuertes and Kalotychou, 2007; Manasse and Roubini, 2005; Jedidi, 2013). In addition, because developing countries experienced debt crisis mostly in the 1960s and 1980s, it is harder to collect the data dating back to these periods for this kind of empirical work. This paper adds to the literature by collecting a relatively long dataset, spanning 1960 to 2017 and covering 43 developing countries, to construct EWSs for these countries.

[2] Schimmelpfennig, Roubini, and Manasse (2003) define debt crisis as a period when a country receives a non-concessional debt exceeding 100% of the quota from the International Monetary Fund (IMF), which the disbursement is made in the first year as a period of the government debt crisis. Dawood, Horsewood, and Strobel (2017) define debt crisis in developing countries as follows: (i) accumulated interest and / or principal exceeding 5% of outstanding debt, (ii) receiving loans from the IMF exceeding 100% of state quota, (iii) cumulative credit from the IMF increases by more than 200% quota, and (iv) conduct debt restructuring or rescheduling more than 20% of outstanding debt

Using the noise to signal ratio and the binomial logit regression methods, we find the following. The binomial logistic regression offers a better predictive power relative to the noise to signal ratio method. The binomial logistic regression model that can predict 61.5% of the government debt crisis 2 years earlier. An increase in inflation, government and private debt exposure, external debt to exports, ratio of short-term external debt to foreign exchange reserves, and the ratio of external interest payments to gross national income can signal an upcoming debt crisis. Similarly, a continous decline in the gross domestic product (GDP) and government consumption also increase the likelihood of government debt crisis. These findings have implications for policies in the 43 developing countries. We highlight these implications in our discussions.

Our study relates to most of these studies, especially Manasse, et.al (2003), Kamra (2013), and Dawood, et.al. (2017), since we employ the logistic regression and the noise to signal ratio methods, and the above-mentioned predictors. The distinctive feature of our study is that it covers a broader range of developing countries. Two prior studies are closely related to this one- Dawood, et.al, (2017) find that an increase in IMF Credit, total debt, and domestic credit, also a decrease in foreign exchange reserve and public spending increase the probability of sovereign crisis. Similarly, Manasse, et.al (2003) find that an increase in debt exposure ratio, low GDP growth and increase in inflation signal debt crisis. The drawback of these two studies is that most developing countries with long period of debt crisis; such as Guyana, Honduras, etc; that appear in Gennaioli, et.al (2014) do not appear in both studies. Hence, we extend these studies by combining countries from both, in addition to new ones. We elaborate this in Section 2. By merging these databases, this study covers more complete episodes of debt crisis for a broader range of developing countries.

The paper proceeds as follows. Section 2 explains the literature review on methods and indicators for predicting government debt crisis. Section 3 explains data and methodology. Section 4 discusses the results. Section 5 provides the conclusions and policy recommendations.

2. Literature Review

Prior studies employ different EWS methodogies to predict government debt crisis. The binomial and multinomial logistic regression method are the commonest (Schimmelpfennig, Roubini, and Manasse, 2003; Dawood, Horsewood, and Strobel, 2017; Kamra, 2013; Engeline and Matondang, 2016).[3] The logistic regression approach entails testing each indicator separately and subsequently including indica-

[3] Others such as Tsai (2013), and Xu, Qi, and Sun (2019) used these models to predict financial distress and crisis.

tors that have good predictive performance together to form a general model. Dawood, Horsewood, and Strobel (2017) find that the binomial logistic model generally performs better than other models such as dynamic signal extraction, binomial logit regression and multinominal logit regression. Others use the signal extraction method to evaluate the performance of individual indicators, both in the form of noise to signal ratio, usefulness ratio, and by maximizing Youden's J-Statistic (Babecky et al., 2014; Fuertes and Kalotychou, 2007). The Bayesian Model Averaging (BMA) (Kamra, 2013), Principal Component Analysis (PCA) (Kamra, 2013), Event Analysis (Balteanu and Erce, 2014), K-means clustering (Fuertes and Kalotychou, 2007), machine learning algorithm such as Artificial Neural Networks (ANNs) (Anwar and Ali, 2018), market pressure approach (Boonman et al., 2015), binary recursive tree analysis (Schimmelpfennig, et.al, 2003), and extreme learning machine technology (Ping et al., 2019) are also used in the literature.

Using these methods, prior studies conclude that a number of indicators are good predictors of government debt crisis including: (i) an increase in the ratio of foreign debt to GDP or total debt to GDP (Dawood, et.al, 2017; Reinhart and Rogoff, 2011; Manasse, et.al, 2003; Akbar, 2018; Jedidi, 2013); (ii) an increase in IMF credit, low government spending, and real exchange rate depreciation (Dawood, et.al, 2017 and Kamra, 2013); (iii) debt-servicing pressure (Kamra, 2013; Drehmann and Juselius, 2014; and Manasse et.al, 2003); (iv) increase in the credit gap against GDP (long term period) and non-core liability (short term period) (Drehmann and Juselius, 2014) ; (v) an increase in the ratio of short-term debt exposure and payment of debt interest exposure (Manasse, et.al, 2003; Gennaioli, 2014); (vi) Significant decrease in GDP Growth (Manase, et.al, 2003; Kamra, 2013; Akbar, 2018; Dreger and Kholodilin, 2018); (vii) a deterioration in macroeconomic measures such as an increase in inflation, or a decrease in export and import (Dawood, et.al, 2017; Jedidi, 2013); and (viii) a sudden stop of the capital outflow which arised from the political issues (Basu, 1993; Warjiyo, 2016). The general message from these studies is that a country with sufficient foreign exchange reserves, high real GDP growth, and a steady inflation can reduce the likelihood of a country's debt crisis. Reinhart and Rogoff (2011) conclude the significance of the increase in inflation against the possibility of a debt crisis. Reinhart (2002) notes that in 1979-1999, 84% of the government debt crisis was preceded by a currency crisis in 60 countries.

3. Data and Methodology

3.1. Data

The study uses an annual data covering the period of 1960 to 2017. This is the longest available sample period. We include 43 developing countries that experienced debt crisis based using the classification by Gennaioli, et.al (2014), and Schimmelpfennig, et.al (2003). Besides, these countries have the most complete data on the crisis indicators. Table 1 shows the countries in our sample, including the crisis periods, the number of crisis, and the average length of the crisis. Table 2 outlines the seven categories of variables included in the analysis.

Table 1: The sample of developing countries and the debt crisis periods

Country	Crisis Periods	Number of Crisis	Crisis Period Average
Algeria	1991 - 1996	1	6
Argentina	1982-1993, 2001-2005	2	8.5
Bolivia	1980 - 1997	1	8.5
Brazil	1983 - 1994	1	12
Bulgaria	1990 - 1994	1	5
Cameroon	1985 - 2003	1	19
Costa Rica	1981, 1983-1990	2	8
Dominica	2002 - 2004	1	3
Dominican Republic	1982 - 1994, 2003, 2005	3	5
Ecuador	1982-1995, 1999-2000, 2008-2009	3	6
Gabon	1986 - 2004	1	7.5
Grenada	2004 - 2005	1	2
Guyana	1982-2004	1	23
Haiti	1981-1993	1	13
Honduras	1981-2004	1	24
Indonesia	1998-2000, 2002	2	1.5
Jamaica	1978, 1987-1993, 2010	3	3.5
Jordan	1989-1993	1	5
Madagascar	1981-2002	1	22
Malawi	1982, 1988	1	1
Mauritania	1992-1996	1	5
Mexico	1982-1990	1	9
Moldova	1998-2002	1	5
Morocco	1983, 1986-1990	2	3
Myanmar	1997-2004	1	8
Nicaragua	1979-2003	1	25
Niger	1982-1990	1	9
Nigeria	1981-1981, 2001	2	6
Pakistan	1997-1998	1	2
Panama	1982-1995	1	14
Paraguay	1981, 1985-1991, 2002-2003	3	3.33
Peru	1977, 1983-1996	2	7.5
Philippines	1982-1991	1	10

Country	Crisis Periods	Number of Crisis	Crisis Period Average
Senegal	1980-1984, 1989-1995	2	3.67
Sierra Leone	1976, 1982-1994	2	4.33
South Africa	1984-1988, 1992	2	1.67
Sudan	1978-2003	1	26
Thailand	1981-1982, 1997-1998	2	2
Togo	1978-1996	1	3.25
Turkey	1977-1983, 2000-2002	2	5
Uganda	1979-1992	1	14
Ukraine	1997-1999	1	3
Zambia	1982-1993	1	12

The table shows the 43 countries in our sample. It shows the crisis periods, the number of crisis, and the average length of the crisis. The classification is based on Gennaioli, Martin, and Rossi (2014), and Schimmelpfennig, Roubini, and Manasse (2003).

Table 2: Data, definitions and sources

Category	Indicators	Measurement
Macroeconomic Conditions	Inflation	Changes in yearly growth of the Consumer Price Index.
	Exchange Rates	US Dollar Exchange rates against domestic currencies, on average in 1 period
	GDP Growth	Yearly growth of the Real GDP (%)
	Export - X_YOY	Yearly growth of the export (%)
	Import - I_YOY	Yearly growth of the import (%)
Private Debt Exposure	Private Credit/GDP	Private credit covers all funding sources in the private sector provided by financial companies include loans, purchases of non-equity securities, trade loans and other account receivables.
	Claims on the private sector	Private sector claims include gross credit from the financial system for individuals, companies, and nonfinancial companies and are not included in net domestic credit, and financial institutions that are not included elsewhere. This variable is calculated as a yearly growth of the percentage of money supply
Foreign Debt Exposure Indicators	External Debt/Export	Ratio of the total stock of external debt to exports of goods, services and primary income (%).
	External Debt/Gross National Income (GNI)	Ratio of the total stock of external debt to GNI (%). Total ULN is total debt to non-residents in cash, goods and services.
Foreign Debt Interest Payment Indicators	External Debt Interest Payment/Gross National Income (GNI)	Ratio of the total interest payment on external debt to GNI (%).
	External Debt Interest Payment/ Export (%)	Ratio of the total interest payment on external debt to exports of goods, services and primary income (%).

Category	Indicators	Measurement
Short-term Foreign Debt Indicators	Short-term external debt/ Export	Ratio of the short-term external debt to export (%). Short-term external debt is external debt with a maturity of less than one year.
	Short-term external debt/ Total Foreign Debt	Ratio of the short-term external debt to total external debt (%)
	Short-Term External Debt / Foreign Exchange Reserves	Ratio of the short-term external debt to foreign exchange reserves (including gold) (%)
Debt Service Ratio Indicators	Debt Service Ratio / Gross National Income (GNI)	Ratio of the Debt Service to the GNI (%). Total debt service is the amount of principal and interest payments in cash, goods and services for long-term debt, payment of short-term debt and repayment to the IMF.
	Debt Service Ratio / Export	Ratio of the Debt Service to the total export (%).
Fiscal Indicators and Government Debt Exposures	IMF Loans (USD)	Total Funding from IMF
	Banking Claims at the Central Government	Claims against the central government (IFS line 52AN or 32AN) including loans to government institutions are central to the net of deposits.
	Government Debt Ratio/ PDB	The ratio of total government debt to GDP.
	Central Government Debt Ratio / GDP	Ratio of the central government debt to GDP (%). Debt is the total stock of government obligations including domestic and foreign obligations such as loans and money deposits, securities other than stocks and loans.
	Government Final Consumption Expenditures	The final government expenditure covers all of the current government expenditure for the purchase of goods and services (including employee salaries).

The table shows the categories, definitions, and sources of the variables used in the study.

3.2. Methodology

We establish the EWSs following a stepwise approach, entailing four methods. We use the t-test for difference in mean in order to see whether the indicators exhibit different behaviors during crisis and normal periods. We support this analysis using an event. This involves a simple regression to understand the evolution of the indicators the period before and after crisis. We, then, test the predictive power of the indicators over government debt crisis using the signaling and binomial logistic regression approach. Noise to signal ratio allows us to understand the predictive power of each indicator, whereas the binomial logistic regression helps establish the joint predictive power of these indicators.

3.2.1. T-Test for Difference in Mean

The t-test for difference in mean, and the event study are our preliminary tests. The test statistic of the null hypothesis that the mean during the crisis period is the same as the mean during the non-crisis period–implying that a variable is not an important indicator of crisis–is calculated as follows:

Equation 1: $$t = \frac{\mu_A - \mu_B}{\sqrt{\frac{S^2{}_A}{\eta_A} + \frac{S^2{}_B}{\eta_B}}}$$

where A and B denote, respectively, the crisis and non-crisis periods; μ_A and μ_B are the averages or means of the indicator or variable in crisis and non-crisis periods, respectively; $S^2{}_A$ and $S^2{}_B$ are the variances of the indicator in crisis and non-crisis periods, respectively; and η_A and η_B denote the number of observations of the indicator during crisis and non-crisis periods, respectively.

3.2.2. Event Analysis

Event analysis is employed to get a more detailed picture of the indicators movement from the normal, pre-crisis, crisis and post-crisis period. The pre-crisis period covers 1 to 3 years before the crisis, the crisis period denotes the first year of the crisis, post-crisis period covers 1 to 3 years after the crisis, and normal period will be all other period. The movement of the indicators will be representated by the mean value of the indicator in each periode. We will run a panel regression using dummy period variables to get a sense of how our indicators behavior change. The coefficient values of each dummy will be added to the constant value to obtain the mean value of the indicator in the corresponding period. The indicator will all be normalized using z-score prior to the regression.

Equation 2: $$Y_i = \beta_0 + \sum_{j=t-3}^{t+3} \beta_{ij} + \alpha i$$

In this equation, β_o will be mean value of each indicator at normal times. Meanwhile, β_{ij} is a constant for each indicator for the dummy period *T-3*, *T-2*, *T-1*, *T+1*, *T+2*, *T+3* and time *T* (first year of crisis) and αi is the country fixed effect.

3.2.3. Noise to Signal Ratio

NTSR will help in identifying which individual indicator can issue signal of crisis. Using NTSR, each value in each period for all indicator will be categorized into one of the 4 categories of signaling matrix as stated in Kamisky, Lizondo and Reinhart (1998) . Value of an indicator is said to issue signal when it breaches the threshold. If the value breaches the threshold and is followed by a crisis, it will be categorized as

A event. When the signal is now followed by crisis, it goes to category B. The third condition is when an indicator doesn't issue signal for an upcoming crisis, it is categorized as event C. While event D counts for any value that doesnt issue signal for no upcoming crisis.

Table 3: Signaling Matrix

	Crisis	Non-Crisis
Signal Issued	A	B
No Signal	C	D

Note: Signaling matrix helps to categorize each indicator behavior towards the set threshold. Indicators which breach the threshold and followed by a crisis after a defined period will be marked as A. Meanwhile, indicators which breach threshold and followed by no crisis will be categorized as B. For indicators which don't breach indicators in any specified period followed by a crisis will be categorized as C and those which followed by no crisis will be categorized as D.

There will be several threshold to be tested, each threshold is calculated by adding indicator's standard deviation to its long-term trend (0.5 to 3 standard deviation with 0.5 increments). Three different prediction period will also be tested, period of one year, two years, and four years before the crisis (Dawood, et, al, 2017). Indicatos which has the most predicted crises and the lowest noise to signal ratio is said to have the ability to predict crisis.

Equation 3: $$\textit{Noise to signal ratio} = (B/(B+D))\ /\ (A/(A+C))$$

Equation 4: $$\%\ \textit{correct crisis} = (A/(A+B))$$

3.2.4. Binominal Logit Regression

We implement the binomial logistic regression as a general model of the EWS government debt crisis. We use the following terms to classify the period into crisis and non-crisis:

Equation 5: $$DC_{it} = \begin{cases} 1 & if\ \exists k = 1, \ldots, h \text{ such that } DC_{i,t+k} = 1 \\ 0 & \text{otherwise} \end{cases}$$

where DC is the binary crisis index (it is 1 for crisis and 0 for non-crisis periods); i and t are country and time subscripts. The crisis period that we employ here is not limited to the first year of crisis only. All period that are identified as crisis period in the literature is denoted with 1. We do this because we don't want to lose any observation, as our dataset is already limited. The logistic model then estimates the likelihood of a crisis using the following formula:

Equation 6: $$\Pr(DC_{it} = 1) = F(X_{it-h}\beta) = \frac{e^{X_{it-h}\beta}}{1 + e^{X_{it-h}\beta}}$$

where X_{it-h} are the indicators with a certain lag, h, and β is a vector of coefficients. The optimal lag is the best NTSR estimate. The data used in the logistic regression is normalized to ensure the comparability. The estimation follows a general to specific approach to construct the general model. That is, the regression is estimated for each group of indicators to establish their importance. Then, all important indicators at the first stage are included in the second stage to form a general model.

4. Results and Discussion

4.1. Summary statistics

Below table summarizes descriptive statistics of our indicators. All of our indicators reject the null hypothesis of unit root under the Fisher test using Augmented Dickey-Fuller (ADF) Test. We apply unbalanced panel data in our analysis, as some countries' data are limited.

Table 4: Summary of Descriptive Statistics

Variable	N	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis	ADF (Inverse chi-squared (P))
Inflation	2107	51.91	466.99	-35.84	11749.64	17.84	368.04	291.69***
Exchange Rate	2389	2.E+10	3.E+11	7.E-05	1.E+13	28.22	879.41	2258.09***
Export	2147	29.09	147.83	-99.99	4640.11	19.15	500.06	415.29***
Import	2230	27.09	132.49	-99.99	3555.13	17.03	360.42	365.43***
GDP Growth (% year-on-year)	2247	3.81	5.13	-26.48	39.49	-0.18	9.18	500.70***
Banking Claims at the Central Government	2219	10.49	20.80	-40.93	272.70	6.66	67.57	325.23***
Private Credit to GDP Ratio (%)	2224	26.94	23.98	1.11	166.50	2.35	10.25	248.47***
Foreign Debt Ratio against Export (%)	1654	284.07	389.44	6.97	4245.39	5.64	43.10	313.07***
Foreign Debt Ratio against Gross National Income (%)	1839	68.74	80.15	0.75	1233.10	6.94	74.60	315.78***
Foreign Debt Interest Payment Ratio against Gross National Income (%)	1839	2.22	2.37	0.00	43.76	5.40	67.21	337.09***
Foreign Debt Interest Payment Ratio against Export (%)	1654	8.13	7.48	0.01	58.91	2.06	9.55	345.94***

Variable	N	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis	ADF (Inverse chi-squared (P))
Short-term external debt ratio against Export (%)	1615	40.35	95.61	0.00	1441.06	8.98	100.49	325.27***
Short-term external debt ratio against Total Foreign Debt (%)	1834	13.90	10.85	0.00	68.69	1.20	4.56	305.29***
Short-Term External Debt against Foreign Exchange Reserves (%)	1688	409.48	2261.10	0.00	59755.56	15.70	338.03	342.47***
Debt Service Ratio against Gross National Income (%)	1808	5.76	5.41	0.00	107.47	6.07	88.99	295.62***
External debt interest payment Ratio against Export (%)	1654	20.37	15.68	0.02	156.86	1.78	9.33	334.43***
IMF Loans (USD)	1642	9.E+08	2.E+09	1.E+04	3.E+10	5.90	47.41	205.49***
Government Debt Ratio to GDP	1936	67.81	85.66	4.50	2092.92	9.61	178.77	342.85***
Claims on the private sector (growth year-on-year as a percentage of money supply)	2204	36.04	319.22	-75.92	11046.93	23.92	713.22	263.05***
Central Government Debt Ratio against PDB (%)	1818	55.87	49.77	2.05	454.86	3.04	17.55	321.73***
Government Final Consumption Expenditures	2058	13.88	7.14	2.98	88.98	4.52	38.59	307.98***

4.2. T-Test for Difference in Mean Results

The results, reported in Table 5, show that the means of almost all the indicators, except credit from IMF and government consumption, are significantly different during crisis and non-crisis periods. This finding is consistent with Dawood, et.al, (2017) who find that IMF credit is not significantly different in developing countries and government consumption is not significantly different in all regions. Specifically, consistent with the findings of Manasse, et.al, (2003), the means of government debt exposure, long-term and short-term foreign debt exposures, foreign debt interest payment obligations, and debt service ratios are significantly higher during the period of crisis. Average private debt indicators tend to be lower during the crisis period. The private debt indicators represent all the credit to the private sector, which is provided by financial institutions. Generally, financial institutions tend to reduce their intermediation and hold their funds in times of crisis. Other important macroeconomic indicators also exhibit significantly different behaviors in the crisis period. Average inflation, exports and imports increase significantly, whereas average exchange rates and GDP decrease significantly during the crisis period.

Table 5: Mean Difference t-test Results

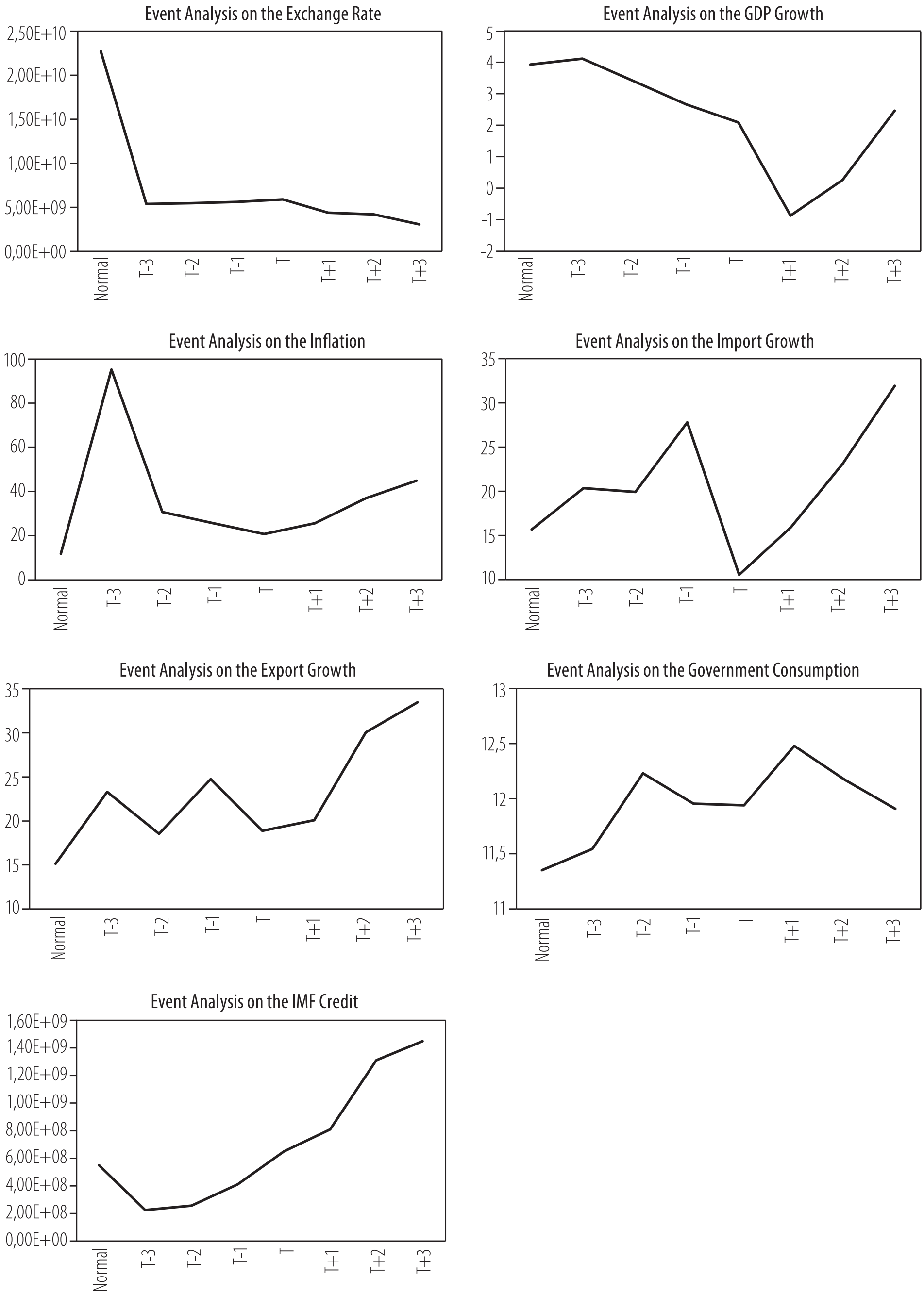
Variables	Non Crisis	Crisis	P-Value Mean Difference
Inflation	14.475	165.277	0.000
Exchange Rate	20300000000.000	44400000.000	0.016
Export Growth	16.015	62.362	0.000
Import Growtn	16.737	55.187	0.001
GDP Growth	3.851	1.719	0.000
Claims on Central Government	7.028	18.854	0.000
Ratio of the Credit to Private Sector to GDP	24.537	21.946	0.013
Ratio of the External Credit to Export	123.470	456.902	0.000
Ratio of the External Credit to GNI	36.263	110.349	0.000
Ratio of the External Credit Interest Payment to GNI	1.194	3.470	0.000
Ratio of the External Credit Interest Payment to Export	3.762	12.129	0.000
Ratio of the Short Term External Credit to Export	14.097	75.864	0.000
Ratio of the Short Term External Credit to Total External Credit	9.330	13.905	0.000
Ratio of the Short Term External Credit to Reserve	67.129	1144.996	0.000
Debt Service Ratio to GNI	3.454	7.169	0.000
Debt Service Ratio to Export	10.679	25.219	0.000
IMF Credit	581000000.000	676000000.000	0.313
Government Debt Ratio to GDP	38.559	110.888	0.000
Claims on Private Sector	13.271	108.637	0.002
Ratio of the Central Government Debt to GDP	34.737	75.700	0.000
General Government Consumption Expenditure	11.369	11.815	0.228

Note: First column shows the mean value of each indicator in non crisis period, while second column shows the mean value of each indicators in the crisis period. Third columen the statistical significance of difference between first and second column.

4.3. Event Analysis Results

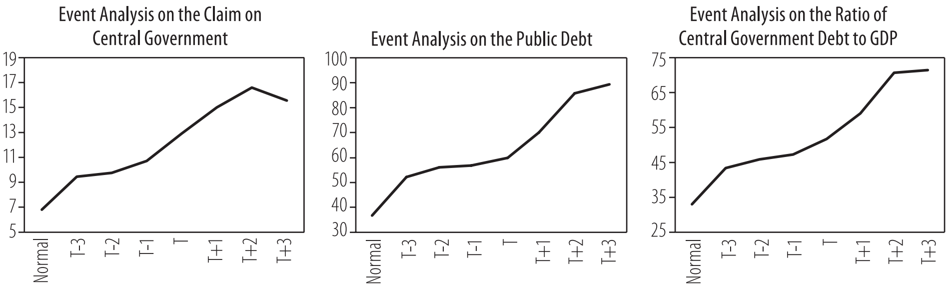
The t-test for difference in mean results are supported by the event analysis in Figure 1. The macroeconomics indicators tend to weaken during the pre-crisis period, T-3. In particular, exchange rates continue to weaken after the crisis, while GDP shows an increase starting from the T + 2 crisis period. Inflation reaches the highest level three years prior to the crisis, declines until the first year of the crisis, and then increases thereafter. Meanwhile, exports and imports show an unpredictable behavior.

Figure 1: Event Analysis of Macroeconomic and Fiscal Variables



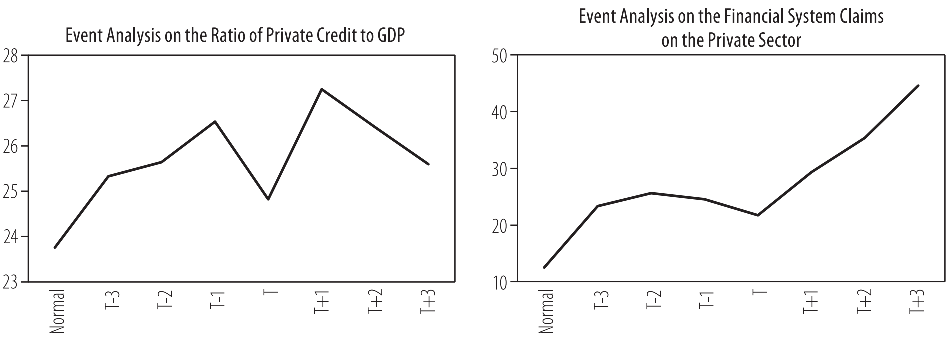
Fiscal indicators also tend to weaken three years before crisis. Government consumption tends to increase three years before the crisis, perhaps showing risk-taking behavior that occur before the crisis. However, it starts to decrease two years until one year before the crisis, showing government funding difficulties. IMF credit shows a slightly different behavior, it tends to increase three years prior to the crisis and continues this path until three years after. This behavior is similar to the Dawood, et.al,(2017) findings.

Figure 2: Event Analysis of Government Debt



Meanwhile, as expected, the indicators of government debt exposure tend to increase starting from three years before the crisis and continue this path until the third year following the crisis. This shows that after the debt crisis, the government still faces difficulties repaying its debts.

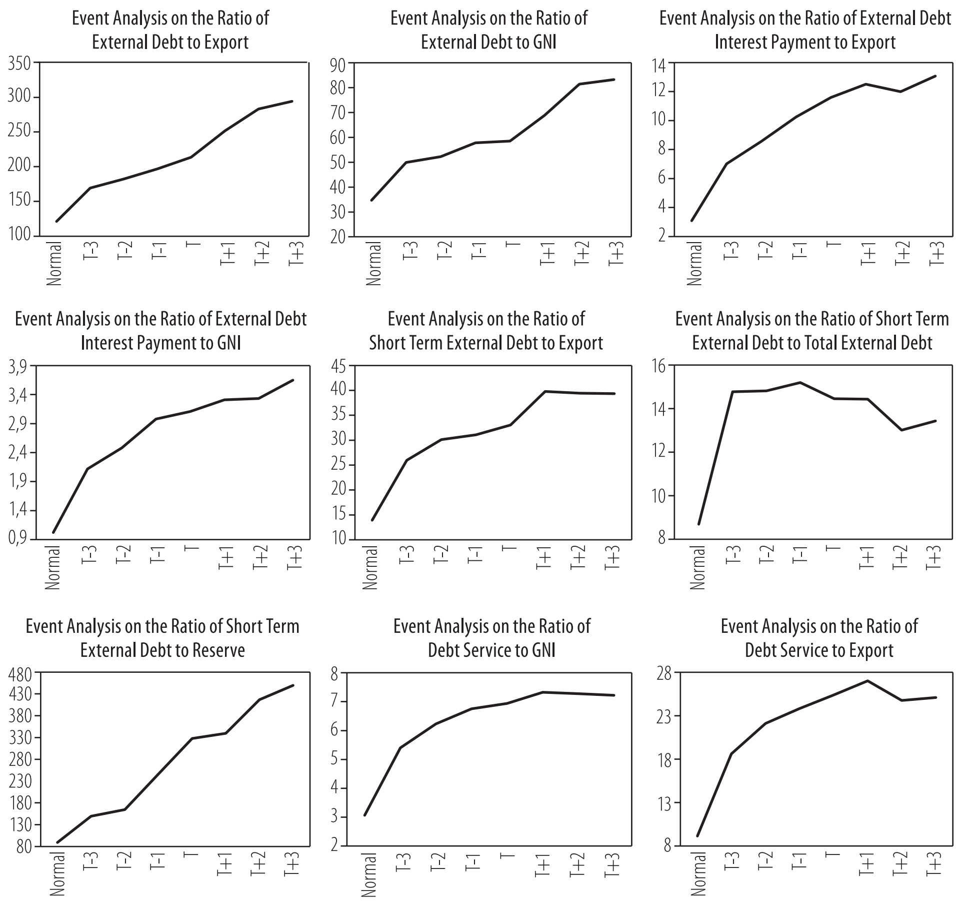
Figure 3: Event Analysis of Private Debt



The private debt exposure indicator shows a different pattern. They tend to increase three years before the crisis and reachs its highest level exactly one year before the crisis. This indicator declined slightly during the crisis and increased again one year after the crisis. The indicators of claims in the private sector increase 3 to 2 years before the crisis, fall slightly during the crisis and then increase after the first year of the crisis.

The common decreasing pattern of these indicators in the crisis period shows the procyclical behavior of financial institutions. In good times, which usually takes place before the crisis, financial institutions flood the market with huge amount of loans, while during the crisis, they withhold their loans.

Figure 4: Event Analysis of Foreign (External) Debt (Total, Interest Payment, Short Term and Debt Service



Furthermore, almost all indicators of foreign debt exposure consistently show significant increase three years before the crisis and continue to grow even higher up to three years after the crisis. This shows the risk-taking behavior that usually takes place before the crisis. Once the crisis hit, countries face difficulties to recover. The main driver is the exchange rate devaluation that leads to an increase in countries external debt burden. This behavior is consistent with Manasse et.al (2003) and Dawood et.al (2017) findings who find that foreign debt exposure remains high even after the crisis.

4.4. Noise to Signal Ratio Results

We employ several combinations of standard deviations and prediction periods. Table 6 reports most optimal results obtained by NTSR with a prediction period of 2 years and 1,75 standard deviation.

Table 6: Results of Noise to Signal Ratio

Variables	Noise	% correct crisis
Inflation	26.30%	48.24%
Exchange Rate	16.34%	60.00%
Export Growth	64.88%	27.42%
Import Growtn	77.85%	23.94%
GDP Growth	84.79%	22.42%
Claims on Central Government	49.02%	33.33%
Ratio of the Credit to Private Sector to GDP	36.76%	40.00%
Ratio of the External Credit to Export	98.04%	20.00%
Ratio of the External Credit to GNI	9.19%	72.73%
Ratio of the External Credit Interest Payment to GNI	15.60%	61.11%
Ratio of the External Credit Interest Payment to Export	24.51%	50.00%
Ratio of the Short Term External Credit to Export	42.89%	36.36%
Ratio of the Short Term External Credit to Total External Credit	49.02%	33.33%
Ratio of the Short Term External Credit to Reserve	57.54%	29.87%
Debt Service Ratio to GNI	27.23%	47.37%
Debt Service Ratio to Export	34.31%	41.67%
IMF Credit	351.29%	6.52%
Government Debt Ratio to GDP	39.83%	38.10%
Claims on Private Sector	73.53%	25.00%
Ratio of the Central Government Debt to GDP	76.59%	24.24%
General Government Consumption Expenditure	252.09%	8.86%

Note: This table summarizes the noise and % of crisis predicted by each individual indicators. We try to find indicators which has at least 60% correct crisis with the lowest noise.

These results show that, individually most indicators do not have a good predictive performance. The indicators that show a good performance are: (i) the ratio of foreign debt to gross national income, which has the highest predictive power of 72.7% with a quite low noise of 9%; (ii) the ratio of interest payments on foreign debt to gross national income, which has 61% predictive power and 15% noise; (iii) and the exchange rate, which is able to predict more than 60% of the crisis with 16% noise. A number of indicators have a moderate predictive power. These indicators are inflation, ratio of interest payment of external debt to export, ratio of debt service to gross national income, and ratio of debt service to export. These indicators have approximately 40% predictive power. However, they have quite high level of noise (more than 20%). The remaining indicators show a poor individual performance in predicting government debt crisis.

4.5. Binomial Regression Logit Results

We now turn to the logistic regression estimates. Table 7 reports these results. The optimal NTSR is obtained with a 2-year prediction period (or a lag of 2 years). The two years are sufficient for authorities to take action once the crisis symptom occurs.

Table 7: Binomial Regression Logit per Indicator Categories

Debt Crisis	-1	-2	-3	-4	-5	-6
Ratio of the Claims on Central Government to GDP	0.307***					
	-4.91					
Government Debt Ratio to GDP	0.951***					
	-9.32					
Central Government Debt/GDP	-0.265**					
	-2.70					
Credit to Private Sector/GDP		0.106*				
		-1.96				
Growth of the Claims on Private Sector		0.215***				
		-4.15				
External Debt/Export			1.023***			
			-11.05			
External Debt/GNI			0.249**			
			-2.78			
Payment on External Debt Interest/GNI				0.327***		
				-3.61		
Payment on External Debt/Export				1.132***		
				-11.99		
Short Term External Debt/Export					0.731***	
					-7.9	
Short Term External Debt/Total External Debt					-0.176*	
					(-1.99	
Short Term External Debt/Reserve					0.686***	
					-7.97	
Debt Service Ratio/GNI						0.101
						-1.15
Debt Service Ratio/ Export						1.184***
						-12.74
N	2295	2407	2407	2407	2239	2407

Note : the table summarizes the results of the binomial logit regressions for each category of indicator. First column summarizes the regression result for Government Debt Exposure Category, second column for Private Debt Exposure Category, third column for External Debt Exposure Category, fourth column for Interest Payment Exposure Category, fifth column for Short Term Debt Exposure Category, and sixth column for debt service category.

We can see that the indicators of government debt exposure, except the ratio of central government debt to GDP that has the opposite direction, show a significant increase. Thus, generally, these indicators will increase significantly 2 years before crisis, marking the risk-taking behavior of the government. Same picture can be seen from all indicators in the private sector credit exposure category. Specifically, external debt exposure, exposure to external debt interest payments, and debt service ratios show high significance in the right direction. These indicators increase significantly 2 years before the government debt crisis. However, the indicators in the short-term external debt exposure category, especially the short-term external debt to total external debt ratio, show the opposite (and counterintuitive) direction.

In the following step, we construct a general model using the significant indicators in Table 7. All indicators that with opposing (or counterintuitive) signs are eliminated in this analysis. The results are reported in Table 8.

Table 8: A General Model for Binomial Logit Regression

Inflation	0.295***
	-3.99
GDP Growth	-0.327***
	-4.51
Claims on Central Government	0.183*
	-2.44
External Debt/Export	0.307**
	-2.89
Short Term External Debt/Reserve	0.604***
	-7.6
Debt Service Ratio/ Export	0.639***
	-5.75
Growth of the Claims on Private Sector	0.148*
	-2
General Government Consumption Expenditure	-0.298***
	-3.54
Payment on External Debt Interest/GNI	0.324***
	-3.56
_cons	-2.243***
	-10.58
lnsig2u	
_cons	0.318
	-1.13
N	2183
t statistics in parentheses	
* p<0.05, ** p<0.01, ***p<0.001	

Note: Values reported are the marginal effects.

The general model includes nine indicators that can significantly predict the occurrence of the debt crisis in the sampled countries. The probability of a debt crisis is increased by an increase in inflation, claim on central government, claim on private sector, ratio of external debt to exports, short-term external debt ratio to foreign reserves, and ratio of external interest payments to gross national income 2 years prior to the crisis. An increase in inflation generally indicates monetary instability, relevant with Dawood, et.al (2017). Similarly, an increase in any debt exposure indicators generally marks risk-taking behavior that can ultimately burden a country's balance sheet or government balance sheet in particular. The significance of debt exposure indicators are strongly relevant to the previous studies of Kamra, (2013), Jedidi (2013), Gennaioli (2013), Dawood, et.al. (2017) and Manasse, et, al. (2003).

Other indicators that can increase the probabiliy of government debt crisis is a decline in GDP and government consumption. A decline in GDP generally marks a contraction in a country's economy. This result is inline with the findings of Kamra (2013), Akbar (2018), and Dreger and Kholdilin (2018). Meanwhile, governments generally tend to reduce their consumption prior to crisis. This happens once governments realize that they have funding difficulties. This finding is also relevant with Dreger and Kholdilin (2018) and Dawood, et.al. (2017).

The Pseudo R^2 is approximately 0.33 with Bayesian Information Criterion (BIC) of 1520.88 and Akaike Information Criterion (AIC) 1458.31. Furthermore, the Hausman test is conducted to find out whether random or fixed effect estimator is appropriate for this estimation. The results of the Hausman test shows that we cannot reject the null hypothesis that the difference in coefficients is not systematic. Hence, the random effects estimator is appropriate in this regard.

Finally, we measure the predictive ability of our model by calculating a predictable crisis process. A 30% cut-off is chosen to reduce the risk of missing a crisis. Policymakers will prefer to have false signals as compared with missing a crisis. Table 9 shows that, based on these calculations, the number of crises that can be predicted is 299/486 = 61.5%.

Table 9: Results of Crisis Prediction

Crisis	Prediction		Total
	0	1	
0	1521	487	2008
1	187	299	486
Total	1708	786	2494

Note: The table represent the number of event which belongs to each category. Based on our binomial logit model, the number of crisis predicted is 299. Divide the number by the total crisis occurence, we get 61.5% correct crisis prediction.

5. Conclusion and Recommendations

Despite the fact that government debt is generally considered to have zero-risk, the suddeness of the previous government debt crises makes the construction of an early warning system important. Previous studies mostly focus on currency and banking crises. Therefore, we bridge the research gap by constructing an EWS that can be used to detect government debt crises.

This research uses panel data from 43 developing countries from 1960 to 2017 with annual data. We use noise to signal ratio to see the performance of individual indicators and binary logistic regression models to compile a general EWS model. Using NTSR, the 2-year prediction period provides optimal results. The indicators that show good predictive performance with a relatively low noises are: (i) the ratio of foreign debt to gross national income, which has the highest predictive power of 72.7% with a quite low noise at 9%; (ii) The ratio of interest payments on foreign debt to gross national income, which has 61% predictive power and 20% noise; (iii) and the exchange rate, which able to predict more than 60% of the crisis with 6% noise. A number of indicators have a moderate predictive power, such as inflation, ratio of interest payment of external debt to export, ratio of debt service to gross national income and ratio of debt service to export. These indicators have approximately 40% predictive power. However, they have quite high level of noise (more than 20%).

Using the binomial logistic regression approach, we find that the general model can predict up to 61.5% of crisis events. The indicators that simultaneously increase the probability of crisis are: GDP, inflation, claims to the central government, external debt to exports, short-term external debt to foreign exchange reserves, debt service ratio to exports, claims to the private sector, external debt interest ratio to gross national income, and government consumption.

The findings suggest that the logistic regression approach can serve policymakers well. Considering the relatively high predictive power of these indicators, we may reccommend authorities to closely monitor them. Any continous increase/decrease in these indicators above their long-term trend may mark symptoms of a crisis. The drawback of this study relates to its sample size and indicators. We focus on developing countries from regions that often do not have complete databases. Hence, we are not able to capture a wider range of indicators. Future studies may improve this shortcoming and add other possible potential indicators.

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