# Predicting Sovereign Debt Crises and Analyzing Their Economic Consequences

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## 1. Introduction

Sovereign debt crises have historically posed significant risks to both developing and developed economies. When countries default on their obligations, it disrupts financial markets, weakens investor confidence, and can lead to prolonged economic stagnation. Past crises, such as the Latin American debt crisis of the 1980s, the 1997 Asian Financial Crisis, and more recently, the Argentine and Sri Lankan defaults, highlight the widespread economic and social consequences of sovereign debt distress.

For this reason, understanding and predicting when a nation is at risk for a debt crisis can be a critical step in preventing or lessening the negative impacts caused by such an event. A significant body of economic literature focuses on exactly this topic to better understand the monetary policy choices that may accelerate sovereign debt crises. National banks and leaders can then use this literature to inform their strategies to protect against such events. In this paper, we focus on two goals: first, to identify key predictors of increased crisis probability using a LASSO-logit regression, and second, to generate a predictive model of sovereign debt crises using machine learning techniques.

## 2. Literature Review

The study of sovereign debt crises has traditionally focused on theoretical models of external debt, beginning with Eaton and Gersovitz (1981) and later extended by Arellano (2008) and Aguiar and Gopinath (2006) to better reflect the realities of emerging markets. More recent work by Bocola et al. (2019) shifts the focus to use total public debt (domestic and foreign) as a predictor, particularly in advanced economies affected by the European debt crisis. By calibrating models to total debt, they more accurately replicate interest rate spreads and crisis dynamics in countries such as Spain, Italy, and Portugal. This shift addresses gaps in earlier models and emphasizes the importance of rising public debt during economic downturns in assessing sovereign risk.

In recent years, empirical researchers have widely adopted Early Warning System (EWS) models to identify default risk. Manasse, Roubini, and Schimmelpfennig (2003) develop both logit and binary recursive tree EWS models, identifying metrics such as foreign debt-to-GDP ratios, short-term debt ratios, slow economic growth, current account deficits, and inflation, as key predictors. While the recursive tree model performs slightly better, the logit model yields fewer false alarms. Expanding on EWS frameworks, Dawood, Horsewood, and Strobel (2017) incorporate crisis duration and regional differences, showing that the predictive strength of indicators like debt-to-GDP ratios and IMF credit varies between developed and emerging economies. This finding supports our use of additional, non-traditional variables to improve our model's predictive accuracy.

Lastly, Fioramanti (2006) explores Artificial Neural Networks (ANN) as a non-parametric alternative to traditional EWS. Using data from 46 emerging countries between 1980 and 2004, the paper demonstrates that a two-layer ANN outperforms traditional EWS models. Inspired by this approach, we apply advanced machine learning techniques—including Extreme Gradient Boosting (XGBoost) and Support Vector Machine (SVM)—to enhance the predictive performance of our sovereign default models.

## 3. Data and Methodology

### 3a. Data Description

The panel dataset used in our analysis comprises 21 countries covering the period from 2000 to 2014. Explanatory variables are collected from the International Monetary Fund (IMF) and the World Bank. These independent variables are sorted into four main categories: external debt metrics, public debt metrics, fiscal indicators, and macroeconomic indicators. Our dependent variable is a binary indicator equal to one if a country experienced a sovereign debt crisis in a given year. This data is collected from the historical crisis and default database produced and maintained by Carmen Reinhart and her co-authors (Reinhart et al.).

In the process of variable selection, we aimed to identify as many relevant predictors as possible to capture the dynamics of sovereign risk. However, several challenges arose, primarily due to the inconsistency of data availability across countries and time periods. Different countries had data available for different years and for different sets of variables, making it challenging to generate a rich dataset containing many countries and indicators. The collected data was very sparse across different indicators for countries at different income levels, making it challenging to create a panel of both developed and developing countries that accurately represents the diversity of national economies. Additionally, we face an issue of class imbalance in our dependent variable because there are far fewer country-years in crisis than those not in crisis.

To address the issue of data selection, we significantly reduced both the set of indicator variables and the time frame considered for our analysis. We focused on selecting variables that had relatively complete coverage while trying to ensure we had a diverse set of indicators that would capture key economic characteristics for our analysis, based on the aforementioned four key categories. This selection process left us with the variables shown in Table 1 of the Appendix. Table 2 provides a list of the 21 countries included in our analysis and their respective crisis periods.

### 3b. Methodology

We use a combination of classical statistical modeling and machine learning techniques to predict sovereign debt crises. Our initial approach uses a logistic regression with year fixed effects to estimate the probability of a sovereign debt crisis. To optimize the logit model, we use LASSO for variable selection. We intend to use this logit model to identify the variables with the most significant correlations with increased likelihood of a debt crisis. Next, we apply machine learning algorithms, including XGBoost and SVM, to focus on prediction accuracy. These techniques offer improvements due to their ability to capture complex relationships between economic indicators and default risks. Additionally, we subset the data into training and testing sets to analyze the performance of the machine learning algorithms. The performance of these methods are evaluated using Precision-Recall Scores (Sensitivity/Specificity) and Receiver Operating Characteristic (ROC) curves, ensuring that our predictions are both reliable and interpretable.

We hypothesize that debt ratios and measures of national fiscal health, such as total reserves and expenditure ratios, will be the strongest predictors of sovereign default in our logit model. In addition, we expect that machine learning algorithms will have better predictive ability than the traditional logit model due to their ability to capture nonlinear relationships in data.

## 4. Analysis & Results

### 4a. Logistic Regression with LASSO Variable Selection

To generate our logistic regression predicting sovereign debt crises, we first fit a LASSO model using cross-validation to select the variables that serve as the best predictors of our outcome variable on our dataset. We then perform a logistic regression with year fixed effects using the variables selected by LASSO. The LASSO-logit regression results are reported in

Table 3 of the Appendix. The coefficients on variables not shown in Table 3 were set to zero by the LASSO selection.

We interpret the logistic regression results as a method of identifying key indicators for increased (or decreased) probability of a sovereign debt crisis. Thus, we focus on the sign and significance of each coefficient, rather than on its magnitude. Our results show that a nation's total debt service ratio, inflation rate, and its current account balance are all significant predictors of the likelihood of a sovereign debt crisis. As expected, our model suggests that when national debt as a proportion of gross income becomes too large, a sovereign debt crisis may be imminent. As confirmed by history, our model also suggests that a higher inflation rate is also a strong signal that the probability of entering a debt crisis is higher. Unexpectedly, a higher current account balance as a ratio of GDP is associated with an increased probability of a sovereign debt crisis. This inverse effect is likely a symptom of our data collection constraints, and may be capturing a trend that exists only between the countries included in our model.

To expand our predictive analysis, we continue by implementing machine learning algorithms and analyzing their out-of-sample predictive power.

**4b. Machine Learning Models: XGBoost and Support Vector Machine**

To enhance the predictive performance of our early warning system for sovereign debt crises, we implemented two machine learning models: Extreme Gradient Boosting (XGBoost) and Support Vector Machine (SVM). These models were chosen for their complementary strengths: XGBoost's ability to handle nonlinear interactions and missing data, and SVM's robustness in high-dimensional settings.

Both models were trained on an 80/20 train-test split of the data using our debt, macroeconomic, and fiscal indicators from the IMF and World Bank. The dependent variable indicates the presence or absence of a sovereign debt crisis, as defined by Reinhart et al.

#### 4b.1. XGBoost Performance

XGBoost achieved an AUC of 0.934, indicating strong discriminative power between crisis and non-crisis observations. The model's accuracy was 92.1%, correctly identifying the majority of "No Crisis" cases. However, its specificity was limited to 20%, suggesting difficulty in detecting actual crisis years, which is a common issue in imbalanced datasets. Still, the model achieved a high sensitivity of 98.3%, ensuring that nearly all non-crisis years were correctly identified. The RMSE was 0.255, and $R^2$ was 0.103, suggesting moderate probability calibration. These results demonstrate that XGBoost is capable of capturing the complex macro-financial relationships underpinning sovereign default risk.

#### 4b.2. SVM Performance

The Support Vector Machine model reached a higher overall accuracy of 96.8%, but failed to identify any true crisis events, resulting in zero true positives and a specificity of 0%. Its high accuracy reflects a bias toward the majority class—non-crisis years—which comprised over 90% of the dataset. The AUC score of 0.95, however, suggests that the model was still able to rank observations correctly in terms of risk. Its RMSE was 0.141, and $R^2$ was 0.006, reflecting a more conservative probability assignment. These results indicate that SVM may be less effective for imbalanced crisis prediction without additional sampling techniques or cost-sensitive adjustments.

### 4b.3. Interpretation

The contrasting performance of these models highlights the challenges of crisis prediction. While SVM achieved higher accuracy, it suffered from class imbalance, failing to capture the rare but crucial instances of sovereign defaults. In contrast, XGBoost provided a more balanced trade-off, demonstrating better overall sensitivity and offering meaningful probability estimates that could serve as inputs for risk monitoring systems.

These findings validate prior literature emphasizing the importance of debt service ratios, fiscal discipline, and external vulnerability indicators. They also support the adoption of machine learning approaches, particularly ensemble models like XGBoost, in early warning systems designed for sovereign debt monitoring.

## 5. Conclusion & Limitations

In conclusion, our traditional logit model and machine learning methods, with the latter focusing on predictive performance, demonstrate solid signaling for sovereign debt crises. Our logit regression highlights the importance of national debt ratios and fiscal indicators in explaining default risk, while the machine learning models focus on predictive ability. However, the study faces two main limitations: data availability and model scope. Limited and inconsistent data restricted the range of countries and time periods we could analyze. Many key indicators were only available for either developed or developing countries, reducing panel balance and coverage.

Another data limitation in this study is the class imbalance between country-years that experienced a sovereign debt crisis and country-years that did not. During our period of study, many more country-years did not experience debt crises than those that did. Because we are working with real-world data in which classes cannot be altered, we are left with models that imperfectly predict sovereign crises in part due to this imbalance.

Additionally, while our models capture key predictors, they do not explain all cases. Default risk is also shaped by debt structure and monetary control. Nations such as Japan avoid default despite high debt due to monetary sovereignty and their ability to borrow in their own currency. In contrast, nations like Argentina and Venezuela borrow heavily in foreign currency, increasing their exposure to exchange rate shocks. Dollarized countries like Ecuador, and Eurozone members like Greece and Portugal, lack the ability to issue their own currency. These examples underscore the importance of monetary control and debt currency, which are factors not fully captured in our model.

References


Aguiar, M. and Gopinath, G. “Defaultable debt, interest rates and the current account.” *Journal of International Economics.* 69(1), (2006): 64-83. https://doi.org/10.1016/j.jinteco.2005.05.005.

Arellano, C. “Default Risk and Income Fluctuations in Emerging Economies.” *American Economic Review.* 98(3), (2008): 690-712. DOI: 10.1257/aer.98.3.690.

Bocola, L., Bornstein, G., Dovis, A. “Quantitative sovereign default models and the European debt crisis.” *Journal of International Economics.* 11, (2019): 20-30. https://doi.org/10.1016/j.jinteco.2019.01.011.

Dawood, M., Horsewood, N., Strobel, F. “Predicting sovereign debt crises: An Early Warning System approach.” *Journal of Financial Stability.* 28, (2017): 16-28. https://doi.org/10.1016/j.jfs.2016.11.008.

Eaton, J., Gersovitz, M. “Debt with Potential Repudiation: Theoretical and Empirical Analysis.” *The Review of Economic Studies.* 48(2), (1981): 289-309. https://doi.org/10.2307/2296886.

Fioramanti, M. “Predicting Sovereign Debt Crises Using Artificial Neural Networks: A Comparative Approach.” *Institute for Studies and Economic Analyses.* Working paper no. 72 (2006). http://dx.doi.org/10.2139/ssrn.935107.

International Monetary Fund, “Debt Sustainability Analyses,” “World Economic Outlook,” Accessed 20 Feb 2025.

Kaminsky, G., Lizondo, S., & Reinhart, C. “Leading indicators of currency crises.” *IMF Staff Papers.* 45(1), (1998): 1-48. https://www.imf.org/external/pubs/ft/staffp/1998/03-98/pdf/kaminsky.pdf.

Manasse, P., Roubini, N., Schimmelpfennig, A. "Predicting Soverign Debt Crises." *International Monetary Fund.* Working paper 03/221 (2003). https://www.imf.org/external/pubs/ft/wp/2003/wp03221.pdf.

Reinhart, C., et al. "Global Crises Data by Country." *Harvard Business School.* https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx.

World Bank, "International Debt Statistics", Accessed 20 Feb 2025.

Appendix

Table 1: Explanatory Variables Selected for Analysis

| | |
|---|---|
| Measures of External Debt | Total Debt Service as a Percentage of GNI |
| | Short-term Debt as a Percentage of Total Reserves |
| | Short-term Debt as a Percentage of Total External Debt |
| | Public Debt Service as a Percentage of GNI |
| | Total Reserves as a Percentage of Total External Debt |
| Measures of Public Debt | Central Government Debt as a Percentage of GDP |
| | Gross Government Debt as a Percentage of GDP |
| Fiscal Variables | Government Revenue as a Percentage of GDP |
| | Government Expenditure as a Percentage of GDP |
| Macroeconomic Variables | GDP Growth Rate (annual) |
| | Inflation Rate (annual) |
| | Exports growth (annual) |
| | Current Account Balance as a Percentage of GDP |
| | Net Foreign Direct Investment as a Percentage of GDP |

Table 2: Crisis Periods by Country

| Country | Crisis Period |
|---|---|
| Algeria | |
| Bolivia | |
| Colombia | 2000 |
| Costa Rica | |
| Dominican Republic | 2003-2004 |
| Egypt | |
| El Salvador | |
| Honduras | |
| Indonesia | 2000-2002 |
| Mauritius | |
| Mexico | |
| Morocco | |
| Nicaragua | |
| Paraguay | |
| Peru | |
| Philippines | 2000-2001 |
| South Africa | |
| Sri Lanka | |
| Thailand | 2000-2002 |
| Tunisia | |
| Turkiye | 2000-2002 |

Table 3: LASSO-Logistic Regression Results

| | (1) |
|---|---|
| Total Debt Service as % of GNI | 1.127** |
| | [0.041, 2.213] |
| Public Debt Service as % of GNI | −0.022 |
| | [−1.346, 1.303] |
| Current Account Balance as % of GDP | 0.294*** |
| | [0.073, 0.514] |
| General Government Revenue as % of GDP | −0.296 |
| | [−0.715, 0.122] |
| FDI Net Inflows as % of GDP | −0.714 |
| | [−2.119, 0.691] |
| Inflation Rate | 0.483** |
| | [0.092, 0.874] |
| Num.Obs. | 105 |
| R2 Adj. | 0.531 |
| R2 Within Adj. | 0.601 |
| RMSE | 0.15 |
| Std. Errors | by: Country |
| Year Fixed Effects | X |

* p <0.1, ** p <0.05, *** p <0.01
Standard errors clustered at the country level. Year fixed effects included.

Table 4: XGBoost and SVM Predictive Power Results

| Model | RMSE | $R^2$ | Accuracy | AUC | Sensitivity | Specificity |
|---|---|---|---|---|---|---|
| **XGBoost** | 0.255 | 0.103 | 92.1% | 0.934 | 0.9828 | 0.2 |
| **SVM (Linear)** | 0.141 | 0.006 | 96.8% | 0.950 | 1.0 | 0.0 |

Figure 1: ROC Curve and Confusion Matrix - XGBoost

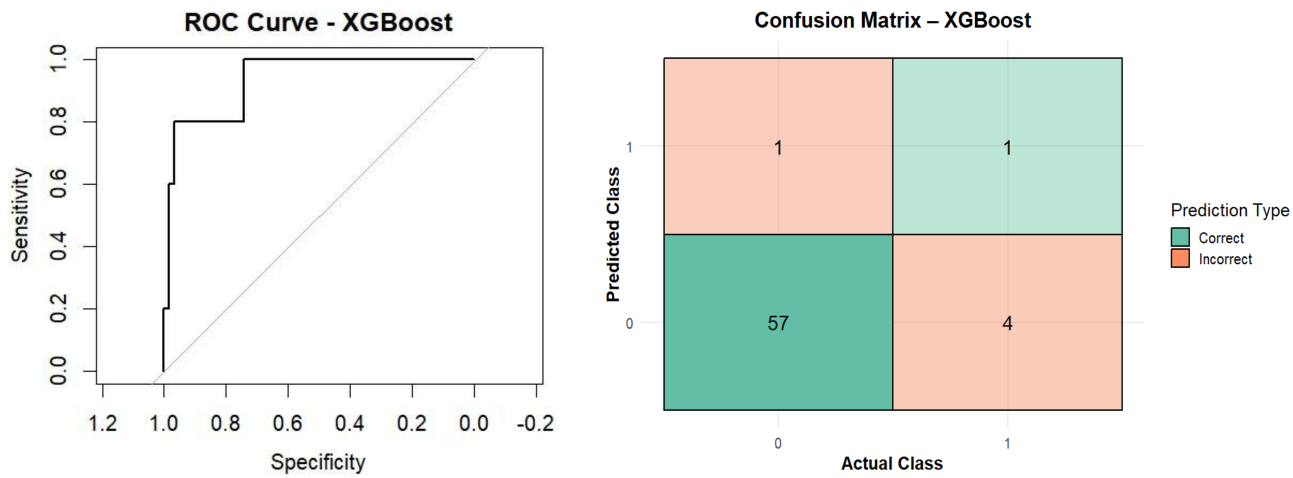


Figure 2: ROC Curve and Confusion Matrix - SVM