Sovereign Default Risk: Prediction and Inference

Haritha GB, Deepak Chaurasiya, Gitika Daswani

SUMMARY: This study addresses the urgent need for more accurate predictive models for sovereign debt crises, which severely impact economic stability and societal welfare by undermining public resource allocation and destabilizing financial systems. Despite numerous models attempting to forecast these events, their predictive power remains inadequate. Our research aims to refine these models by incorporating a broader set of financial and economic indicators, enhancing both predictive accuracy and inferential capabilities. By analyzing external debt levels, foreign exchange reserves, and the ability to service debt with export revenues among other indicators, we propose a novel approach to forecasting fiscal stress events. This paper contributes to the scholarly dialogue by offering a more reliable tool for anticipating sovereign defaults, thereby aiding in the mitigation of their potentially devastating effects.

1. INTRODUCTION

The phenomenon of sovereign default, historically perceived as a rarity within the global financial ecosystem, has emerged as a critical area of concern following a series of high-profile defaults over the past decades. These events have not only debunked the myth of sovereign immunity to bankruptcy but have also highlighted the intricate web of factors contributing to such financial crises. From Argentina's monumental $132 billion default in 2001 to Zambia's default in the wake of the COVID-19 pandemic, each case of sovereign default provides unique insights into the interplay of economic mismanagement, policy failure, external shocks, and structural vulnerabilities.

A fiscal crisis typically manifests through the breakdown of the exchange rate mechanism or the destabilization of the banking sector, unfolding progressively from a debt crisis into a monetary and subsequently a broader financial crisis. This escalation touches various facets of the economy, ultimately culminating in a widespread economic catastrophe characterized by significant harm. Unchecked debt accumulation poses a grave threat to economic stability. The trajectory from fiscal instability to an all-encompassing economic crisis underscores the interconnected nature of financial systems, where issues in one area can rapidly permeate through to others, amplifying the overall impact. This pattern of crisis development highlights the critical need for vigilant monitoring and management of debt growth to prevent its detrimental effects on the economy.

This research endeavors to dissect the complexities surrounding sovereign defaults through a quantitative lens, aiming to construct a comprehensive predictive framework that can anticipate such events with high accuracy. The objective is twofold: to contribute to the academic discourse on sovereign risk assessment by integrating advanced statistical methodologies, and to offer practical tools for policymakers, investors, and international financial institutions to mitigate the repercussions of sovereign defaults.

By bridging the gap between quantitative analysis and practical financial policy, this study aspires to make a contribution to the field of credit default analysis. The development of a predictive framework for sovereign default is paramount, given the multifaceted triggers such as credit events including sovereign debt defaults, rescheduling, or restructuring that result in substantial losses for debt holders; special financing situations exemplified by loan or financial adjustments by the IMF exceeding 100% of a country's quota; implicit domestic public default signaled by high inflation rates or surges in domestic debt; and the erosion of market confidence manifested through escalated financing costs or the incapacity to secure financing on the international capital market. To this end, study aims to build a predictive model to capture drivers of sovereign fiscal crisis.

2. RELATED WORK

There have been several notable studies, in the domain of sovereign risk prediction, attempting to understand the nature of risk leading to such default and further predicting such defaults in the future.

As early as 2008, Fioramanti et al. (1) attempted to predict financial crises, focusing on sovereign debt crises in developing countries. Their research emphasizes the effectiveness of artificial neural networks (ANN), in Early Warning Systems (EWS). Analyzing data from 1980 to 2004, they show that ANN-based EWS outperforms traditional parametric models. (1) claims that ANNs' flexibility enables them to capture non-linear relationships, potentially offering more accurate and timely signals of impending crises, thereby enhancing financial risk management strategies.

With the intent of focusing on a different set of explanatory variables, Szetela et al. (2) utilized multivariate discriminant analysis (MDA) to differentiate between defaulted and non-defaulted nations, based on macroeconomic signals. Their findings underscore the predictive power of non-liquid macroeconomic indicators in identifying sovereign solvency issues. On the other hand, OH et al. (3) proposed to analyze sovereign credit rating migration dynamics using the Regime-Switching Markov Chain (RSMC) model. Their research demonstrates the superior forecasting performance of RSMC, particularly in identifying downgrades during economic contractions and forecasting credit rating movements for various nations. Their findings indicated that in the case of economic recession, countries with worse ratings received a higher probability of downgrading.

Regarding a sovereign default event as the period when a country exceeds the limit of non-concessional IMF lending, Wijayanti et al. (4) developed an early warning signal (EWS) for government debt crises, utilizing panel data from developing countries. Their study highlights indicators such as inflation, debt exposures, and GDP decline as key predictors of impending debt crises, providing valuable insights for policymakers.

Using an interpretable model, Alaminos et al. (5) for sovereign debt and currency crises, employing various computational techniques to enhance precision. Their research emphasizes geographic diversity in samples and underscores the superiority of computational techniques over traditional statistical methods.

Working with more complex time-series models, Zhou et al. (6) explored the relationships between fiscal crises and economic indicators using a comprehensive fiscal crisis risk index system. Their predictive analysis, based on deep neural network models, highlights the nuanced dynamics of fiscal crises across different economies, emphasizing factors such as GDP growth, inflation, and foreign direct investment. Going over the literature, we found Zhou et al. research to be comprehensive in their method of establishing if a country is in distress. Although there methodology achieves good precision, there formulation of fiscal crisis is something that could be improved upon.

3. METHODOLOGY

To achieve our objective, the study employs a variety of quantitative techniques, including machine learning algorithms like (KNNs, SVMs, and Random Forest) and data analytics to analyze a dataset comprised of macroeconomic indicators, financial metrics, and socio-political variables. This section details the data collection methodology, exploratory analysis of the data, predictive modeling efforts and results, and the inferences we can make from such a model.

3.1. Dataset

For our dataset, we attempt to replicate Zhou et al. (6) methodology of data collection. Combining the WEO (World Economic Outlook) and IFS (International Financial Statistics) database of the International Monetary Fund, the WDI (World Development Indicators) and GDF(Global Development Finance) database of the World Bank, we identified 140 countries with enough signals with insignificant noise. Further, we employ the methodology to label sovereign fiscal crises as mentioned in Gerling et al., which defines a quantitative method to label credit events, special financing, domestic public default, and loss of market confidence. Further, it states that if at least one event occurs in the following 4 items, it indicates a fiscal crisis in the country. Due to the unavailability of labels and synchronous data, we limit our modeling scope to years ranging from 1999 to 2015.

To analyze the difference in the behavior of various countries we group all the countries into four broad groups: 1) Advanced Markets (AMs), 2) Emerging Markets (EMs), 3) Low Income Developing Markets (LIDMs) and, 4) Slow Developing Markets (SDSs).

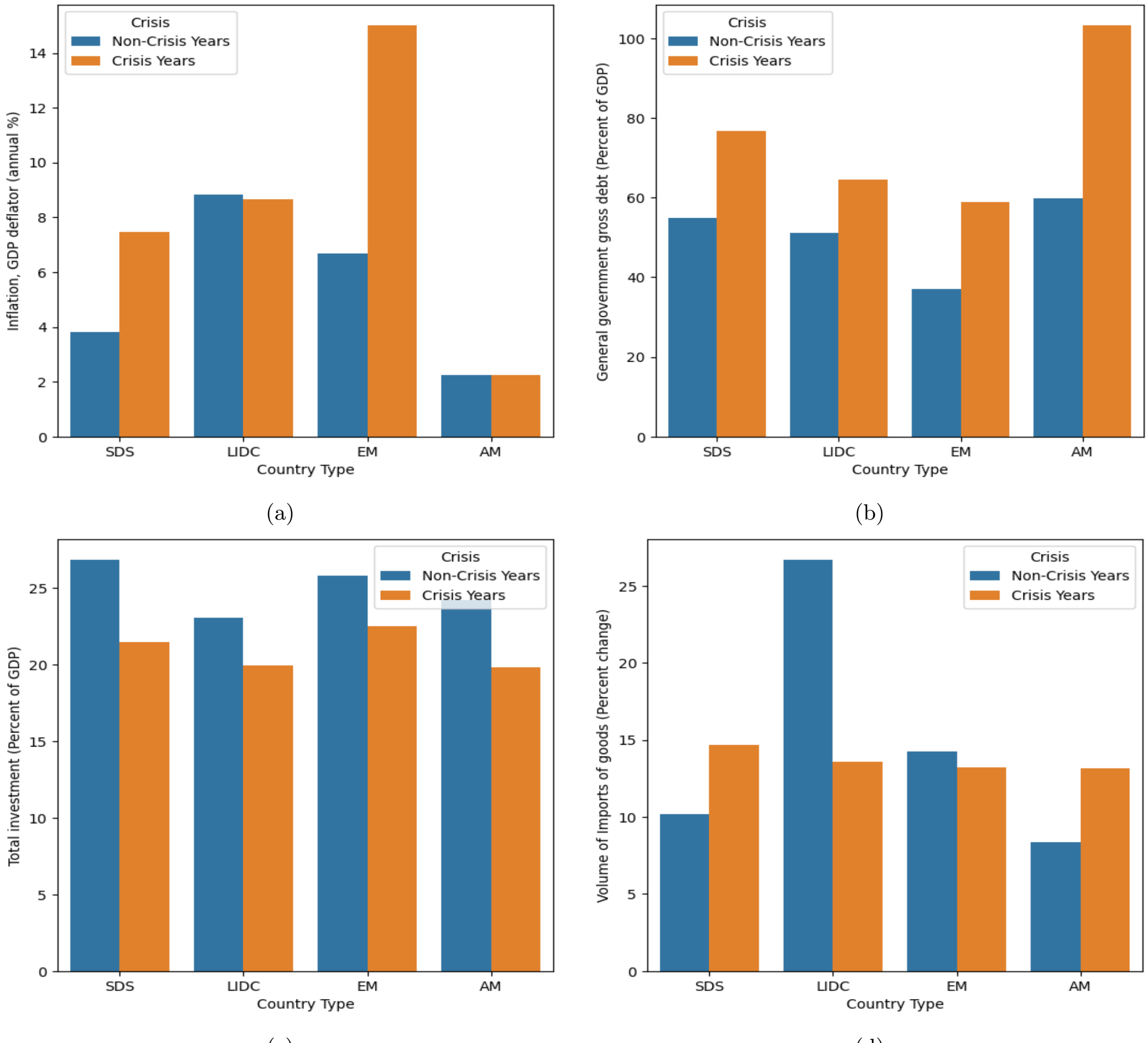
We outline the crisis statistics of the selected countries and duration in table 1. The analysis of fiscal crisis data across distinct country categories unveils notable disparities and trends, providing crucial insights into the dynamics of economic stability. The EM and LIDC categories exhibit a higher frequency of crises compared to the AM and SDS categories, with the EM category experiencing the most significant crisis count (240). Intriguingly, while the EM category endures prolonged crisis durations (6.00 years), the SDS category reports shorter durations (3.50 years). These findings underscore the complex interplay of factors influencing fiscal resilience, necessitating tailored policy interventions to mitigate crisis impact effectively.

3.2. Exploratory Data Analysis and Feature Engineering

Feature Analysis: We analyze certain 4 primary indicators - 1) *Inflation, GDP deflator (annual %)*, 2) *General government gross debt (Percent of GDP)*, 3) *Total investment (Percent of GDP))*, and 4) *Volume of Imports/Exports of goods (Percent change)* for countries grouped by their social and economic development status. Changes in these features when

Country Type	Country count	Crisis Count	Avg. duration of crisis (yr.)
AM	22	84	4.88
EM	36	240	6.00
LIDC	58	210	5.39
SDS	30	20	3.50

Table 1: Fiscal Crises of Countries (1999-2015)



(a) (b) (c) (d)

Fig. 1: Comparative analysis of financial indicators for country groups during crisis

a country is undergoing a fiscal crisis and how they differ across various categories are discussed below.

3.2.1. Inflation, GDP deflator (annual %)

This feature reflects annual changes in an economy's overall price level. In our analysis, as shown in Figure 1a, we observe notable variations in inflation rates across different types of countries during both crisis and non-crisis years. Notably, during crisis periods, inflation tends to escalate across all country categories, albeit to varying degrees. This suggests a commonality in the inflationary response to economic turmoil, irrespective of a country's economic classification. Furthermore, distinctions emerge between country types concerning baseline inflation levels and the magnitude of inflationary spikes during crises. For instance, LIDCs exhibit relatively high inflation rates during non-crisis years, while SDSs and AMs maintain lower and more stable inflation levels. However, during crises, the inflationary surge is more pronounced in SDS and AM compared to LIDC.

3.2.2. General government gross debt (Percent of GDP)

The analysis of the "General government gross debt (Percent of GDP)" figures illuminates compelling insights into the fiscal dynamics of various country types during both crisis and non-crisis periods. The data reveals a consistent trend of elevated government debt levels as a percentage of GDP across all country categories during crisis years compared to non-crisis years. From Figure 1b, one can note that, AMs and SDSs exhibit the most pronounced increases in government debt during crises, with debt levels surpassing 100% of GDP in crisis years for AM. This suggests a heightened reliance on borrowing and deficit spending by governments in these regions to mitigate the adverse effects of economic downturns. LIDCs and EMs also experience notable increases in government debt during crises, albeit to a lesser extent than AM and SDS.

3.2.3. Total investment (Percent of GDP)

The examination of "Total investment (Percent of GDP)" figures unveils intriguing insights into investment dynamics across different country types during both crisis and non-crisis periods. Notably, Figure 1c reveals a consistent trend of decreased total investment as a percentage of GDP across all country categories during crisis years compared to non-crisis years. This decline in investment during crises suggests a cautious approach among investors and reduced capital expenditure by businesses, likely stemming from heightened economic uncertainty and constrained financial conditions. Interestingly, AMs exhibit a more pronounced decrease in total investment during crises than other country types, indicating a heightened sensitivity to economic downturns in these regions.

3.2.4. Volume of Imports/Exports of goods (Percent change)

The analysis of mean percent change in the volume of imports and exports of goods across diverse country types during both non-crisis and crisis years provides nuanced insights into trade dynamics amidst economic fluctuations. Figure 1d shows that, crisis years witness a notable surge in mean percent change in imports across all country categories, suggesting heightened demand or dependence on imports amid economic downturns. Conversely, export volumes display varied responses, reflecting the intricate dynamics of export-oriented sectors influenced by global demand, competitiveness, and trade policies. AMs notably increase import volumes during crises, possibly indicating increased reliance on imports for domestic consumption or production inputs. LIDCs experience a marked decrease in export volumes during crises, indicating vulnerability to external shocks in export-driven economies. These findings underscore the intricate nature of trade dynamics during economic instability and advocate for tailored policy interventions to bolster trade resilience and mitigate the adverse effects of crises on global trade.

Principal Component Analysis (PCA): Principal Component Analysis (PCA) is a statistical procedure that utilizes orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This technique, fundamentally a dimensionality reduction tool, is widely used in exploratory data analysis and for making predictive models. It helps in identifying patterns in data based on the correlation between features. The first principal component has the highest variance and accounts for as much of the variability in the data as possible, with each succeeding component having the highest variance possible under the constraint that it is orthogonal to the preceding components.

Key features of Principal Component Analysis (PCA) include dimensionality reduction, which streamlines the dataset by distilling it to its essential aspects and simplifies the complexity inherent in high-dimensional data. Visualization is another notable feature, as PCA facilitates the graphical representation of complex datasets, aiding in the recognition of patterns and illustrating the relationships within the data. Additionally, PCA is instrumental in noise reduction; by prioritizing components based on variance, it filters out the less variable noise, ensuring that the signal within the data is more prominently featured. These features collectively enhance data interpretability, providing

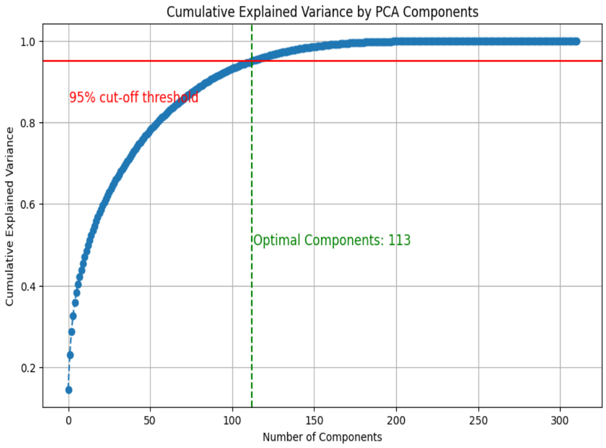


Fig. 2: PCA: Explained Variance v/s Components

a robust foundation for subsequent analysis.

Upon standardisation of the dataset, PCA revealed that a reduced number of 113 components accounted for 95% of the cumulative explained variance. This dimensionality reduction preserves the bulk of information within the dataset while simplifying its complexity, thus allowing for more efficient computational processing in subsequent analytical procedures.

Figure 2 illustrating this finding indicates a plateau beyond the 113-component mark, suggesting that the inclusion of additional components does not substantively contribute to explaining the dataset's variance. This observation substantiates the selection of 113 components as a point of parsimony, balancing the retention of meaningful data against the risk of overfitting associated with extraneous dimensions.

3.3. Model Development and Evaluation

Leveraging the predictive capabilities of machine learning algorithms, we aim to develop a neural network model that harnesses the complex relationships between various financial and economic indicators relevant to sovereign debt. This strategic approach is designed to exploit the full spectrum of data-driven insights, thereby optimizing the model for the accurate prediction of sovereign debt risk.

To ascertain the model's effectiveness, extensive testing will be conducted using a comprehensive set of performance metrics, including accuracy, precision, recall, and the F1 score. This rigorous evaluation process ensures the model's reliability and adaptability in accurately predicting sovereign debt risk, reflecting the intricate dynamics of global financial markets.

3.3.1. Support Vector Machines

Support Vector Machines (SVM) represent a potent supervised learning model utilized for classification and regression tasks. Fundamentally, SVM constructs a hyperplane or set of hyperplanes in a high-dimensional space, which can be used for classification, regression, or other tasks. The optimal hyperplane is the one that exhibits the largest margin between the two classes in the training dataset, hence maximizing the margin of separation between classes. SVMs are particularly renowned for their ability to handle high-dimensional data efficiently and for their versatility, as they can be adapted through the kernel trick to solve linear and non-linear problems alike.

Key features of Support Vector Machines (SVM) include margin maximization, the kernel trick, and regularization. Margin maximization refers to SVM's strategy of maximizing the margin between classes, which contributes significantly to its robustness in classification tasks. The kernel trick allows SVM to effectively handle non-linear data by applying linear classification techniques within a transformed feature space. This makes it possible to classify datasets that are not linearly separable in their original space. Furthermore, SVM incorporates regularization through its regularization parameter, which mitigates the problem of overfitting. This enhancement of the model's generalization capabilities is crucial for achieving high performance on unseen data.

3.3.2. K Nearest Neighbors

K-Nearest Neighbors (KNN) is a simple, yet effective algorithm used in statistical pattern recognition and machine learning for both classification and regression tasks. Unlike SVM, which is a discriminative model, KNN is a type of instance-based or lazy learning algorithm, where the function is only approximated locally, and all computation is deferred until function evaluation. It operates on the principle that similar instances tend to be within close proximity to one another. In KNN, the output is determined by the majority vote of its k-nearest neighbors, with the object being assigned to the class most common among its k nearest neighbors.

Key features of the K-Nearest Neighbors (KNN) algorithm include its simplicity and ease of implementation, flexibility, and sensitivity to the local data structure. KNN stands out due to its straightforwardness, being easy to understand and implement without requiring an explicit training phase, making it accessible for beginners and efficient for rapid prototyping. Its flexibility is evident as it can be adeptly applied to both classification and regression tasks, showcasing its adaptability to different types of data problems. However, KNN's strength—making predictions based on the local data structure—also introduces a notable challenge. While this allows KNN to be highly responsive to the specific characteristics of the data, it also means the algorithm may be sensitive to noisy or irrelevant features, which can adversely affect its performance unless careful feature selection or preprocessing is conducted.

3.3.3. Random Forests

Random Forests stand as a robust and versatile ensemble learning method used for both classification and regression tasks, which operates by constructing a multitude of decision trees at training time. This method, introduced by Leo Breiman in 2001, addresses the problem of overfitting that plagues individual decision trees, thereby significantly improving the predictive accuracy and robustness of the model. The fundamental principle of Random Forests lies in the integration of predictions from multiple decision trees to decide the final output, rather than relying on the output of a single tree. This approach is known as "bagging" or Bootstrap Aggregating.

The Random Forest algorithm is characterized by several key features, including its ensemble learning method, capability to handle high dimensionality, and versatility and ease of use. As an ensemble learning method, Random Forests mitigate the risk of overfitting by aggregating the predictions of multiple decision trees, thereby enhancing the model's generalization ability. This approach not only improves prediction accuracy but also provides a measure of confidence in the predictions made. Furthermore, Random Forests are adept at managing datasets with a high number of features without the need for extensive feature selection. This capability makes it particularly suitable for applications in complex domains where predictive accuracy is paramount. Additionally, the versatility of Random Forests is evident in their applicability to both classification and regression tasks, with implementations readily available in most statistical software packages. Their relative simplicity in terms of parameter tuning makes Random Forests accessible to practitioners across various levels of expertise, underscoring their ease of use and broad applicability in the field of machine learning.

4. Results

The analysis depicted in Figure 4 identifies the most critical features for predicting sovereign defaults using a Random Forest model, across all country groups. Funds held in US dollars top the list as the foremost predictor. Other significant features include a country's currency holdings relative to its quota and its IMF reserve position in SDRs. These elements underscore the role of a nation's financial resources and obligations in the context of international finance. The figure provides a clear, ordered visualization of feature importance, simplifying the complexity behind sovereign default predictions and facilitating a straightforward interpretation.

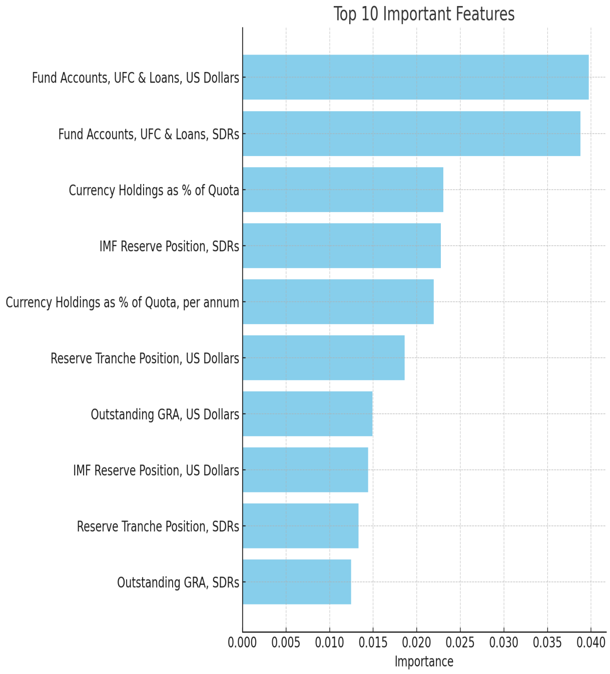


Fig. 3: Feature Importance for Predicting Sovereign Defaults

As illustrated in Figure 4, the extraction of the most crucial economic features across different country classifications—namely Advanced Markets (AM), Emerging Markets (EM), Low-Income Developing Markets (LIDM), and Slow Developing Markets (SDS)—has been conducted with a focus on identifying the most impactful and novel predictors where similarities in importance were observed.

The figure 4 presented delineates the significance of various economic features in the context of different country classifications—Advanced Markets (AM), Emerging Markets (EM), Low-Income Developing Markets (LIDM), and Slow Developing Markets (SDS). In Advanced Markets, government debt as a percentage of GDP (0.04) and GDP per capita, both in purchasing power parity (PPP) and US dollars (0.04 and 0.05, respectively), emerge as the most influential factors. This indicates that for AM, the state of government finance and the relative wealth of individuals are paramount for predictive analysis. In Emerging Markets, GDP per capita in US dollars (0.02) serves as the leading indicator, suggesting that individual economic output is a central consideration in forecasts. FDI net inflows also play a significant role (0.01), indicating the importance of foreign investments in these economies.

For Low-Income Developing Markets, agriculture value added as a percentage of GDP (0.01) and de-

Support Vector Machines

	Precision	*Recall*	*f1-score*
0	0.82	0.70	0.76
1	0.61	0.75	0.67

K Nearest Neighbours

	Precision	*Recall*	*f1-score*
0	0.74	0.76	0.75
1	0.60	0.57	0.58

Random Forests

	Precision	*Recall*	*f1-score*
0	0.69	0.95	0.79
1	0.77	0.30	0.43

Table 2: Accuracy Metrics

	SVM	KNN	RF
ROC-AUC (Cross-validated)	0.78	0.72	0.83
Accuracy	0.72	0.69	0.70

Table 3: Accuracy Metrics

posit money bank assets as a percentage of GDP (0.01) hold the most weight. The prominence of agriculture suggests a reliance on primary sector activities, while the size of bank assets highlights the role of financial institutions in LIDM. Finally, in Slow Developing Markets, GDP per capita, measured in constant 2015 US dollars (0.07), and currency holdings as a percentage of quota (0.05), are the most influential. These indicate that despite slower development, there is a significant emphasis on maintaining stable economic output and currency stability, possibly to ensure sustained growth and manage inflationary pressures.

The identified features underscore the nuanced economic landscapes across different market types and their implications for predictive economic modeling. The emphasis on GDP per capita across classifications underlines the universal importance of individual economic prosperity, whereas the varying significance of other factors reflects the unique economic structures and priorities within each market category.

In the realm of sovereign default prediction, the nuanced performance of each model—Support Vector Machines (SVM), K Nearest Neighbours (KNN), and Random Forests (RF)—carries significant implications for policymakers, investors, and researchers. Given the critical nature of accurately forecasting sovereign defaults, it's paramount to delve deeper into how each metric informs us about the practical utility of these models.

The SVM model, with its precision scores of 0.82 for class 0 (non-default) and 0.61 for class 1 (default), demonstrates a strong capability in correctly identifying non-default cases but is less reliable for default predictions. Its recall scores—0.70 for non-defaults and 0.75 for defaults—indicate a balanced sensitivity to both classes, suggesting SVM could be particularly useful in scenarios where avoiding false negatives (failing to predict a default) is as crucial as avoiding false positives. Given the high cost of a missed default prediction, such as unexpected financial losses or crisis management challenges, the balance SVM offers makes it a reliable choice in environments where precision in identifying non-default cases and recall in default scenarios are both valued.

KNN presents a more balanced picture, with slightly lower precision and comparable recall scores to SVM. The somewhat moderate f1-scores (0.75 for non-defaults and 0.58 for defaults) suggest KNN's overall efficacy in handling both classes is moderate. This balance might make KNN suitable for preliminary analysis or situations where computational simplicity and interpretability are prioritized over the highest predictive accuracy. However, the slightly lower performance metrics, particularly in identifying default cases, might limit its applicability for critical financial decision-making.

Random Forests show a distinct pattern, with a notable discrepancy between high recall for non-defaults (0.95) and significantly lower recall for defaults (0.30). While the model is highly effective in identifying non-default cases (as indicated by the recall), its lower precision for default predictions might raise concerns in applications where missing a default prediction carries heavy penalties or risks. However, Random Forest's highest ROC-AUC score (0.83) suggests it has the best capability among the three models to distinguish between default and non-default cases across various threshold settings, making it potentially the most robust model for complex datasets or scenarios where the cost of false positives is lower than that of false negatives.

The practical implications of these findings are profound. In choosing the best model for sovereign default prediction, one must consider the specific context and objectives. For instances where missing a default prediction can lead to significant financial or political repercussions, a model with a high recall for defaults might be preferred. On the other hand, if the focus is on minimizing false alarms to avoid unnecessary market panic or policy responses, a model with high precision for non-defaults would be more suitable. Given these considerations, Random Forest emerges as a strong candidate for its superior ability to differentiate between classes, despite its lower precision for default predictions, making it particularly useful for comprehensive risk assessment frameworks that prioritize the early detection of potential defaults.

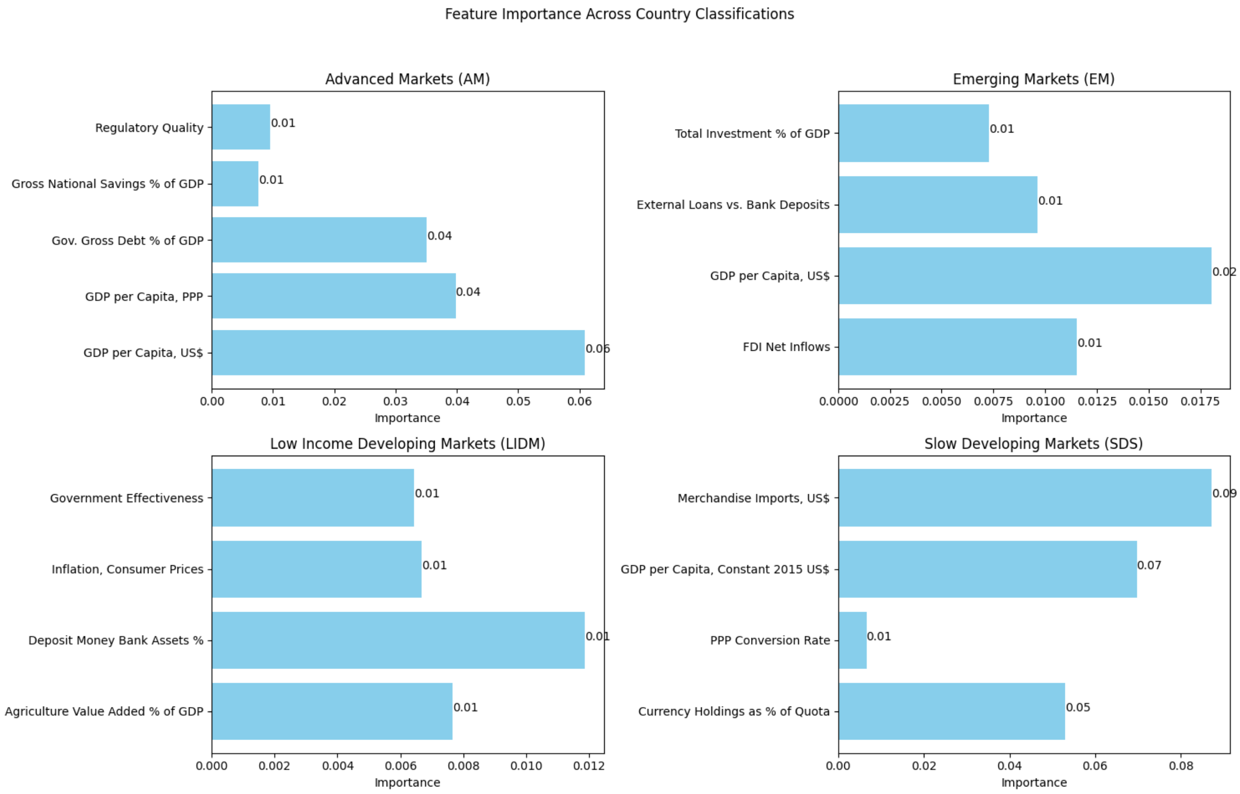


Fig. 4: Feature Importance Across Country Classifications

5. Model Validation

As mentioned in Section 3.1, we only focus on data from 1999-2015 for the 140 countries due to the absence of fiscal crisis labels. Now, to verify the efficacy of our model, we collate the features for these countries for 2016-2021 and note the prediction of our random forest model. We aim to manually verify if the top 5 countries identified by our model as highly likely to suffer a fiscal crisis came to fruition.

We present the model predictions in Table 4. The model identifies Bosnia, Pakistan, Seychelles, Ukraine, and Greece as the top 5 sovereigns vulnerable to a financial crisis in the mentioned years. Reading financial reports and articles about these nations, it is clear that these countries have faced drawbacks in their financial stability journey over the past decade. Bosnia faced challenges due to ethnic tensions and structural weaknesses in its economy. Pakistan grappled with fiscal deficits, political instability, and security concerns. Seychelles experienced a debt crisis exacerbated by overborrowing and weak fiscal management. Ukraine faced geopolitical tensions and corruption issues, exacerbating economic vulnerabilities. Greece's crisis was characterized by unsustainable public debt, fiscal mismanagement, and structural weaknesses in its economy, leading to a sovereign debt crisis and bailout packages from international creditors.

At the same time, countries like Singapore, Denmark, Portugal, Slovenia, and Luxembourg are deemed to be the safest by the models. These countries have boasted a stable economic standing over the past decade and the model has done very well in identifying that. Looking at these examples, one can be confident that the financial signals fed to the Random Forest model are capable of capturing fiscal crisis risk.

6. CONCLUSION

This study endeavours to refine the predictive modeling of sovereign defaults, building on the foundational methodology established by Zhou et al. (6). Our approach diverges from traditional singular event-based definitions of fiscal crises, opting instead for a nuanced, multi-classification scheme. Here, the presence of multiple indicators—Credit Events, Special Financing, Implicit Domestic Public Default, and Loss of Market Confidence—is not aggregated into a singular risk metric. Rather, each event is evaluated both independently and in combination, providing a granular assessment of sovereign default risk.

This multi-faceted definition aims to capture the complex dynamics and co-occurrence of risk indicators, offering a more accurate and nuanced model of fiscal crisis prediction. The adoption of this approach

Country	Year	Probability	Category
Bosnia and Herzegovina	2016	0.89	Top - 5
Pakistan	2016	0.87	
Seychelles	2016	0.84	
Ukraine	2018	0.82	
Greece	2016	0.81	
Luxembourg	2021	0.0	Bottom-5
Slovenia, Rep. of	2016	0.0	
Portugal	2019	0.0	
Denmark	2018	0.0	
Singapore	2016	0.0	

Table 4: Top and Bottom most vulnerable countries as identified by the Random Forest model

is predicated on the availability of high-quality, extensive datasets, enabling a comprehensive analysis of the interplay between various risk factors. By enhancing the granularity of risk assessment, this study seeks to contribute significantly to the field of economic risk management, aiding policymakers, investors, and researchers in navigating the intricate landscape of sovereign finance with greater precision and insight.

In sum, our proposed methodology not only challenges conventional models with a more sophisticated framework but also underscores the importance of a detailed, event-specific analysis in understanding and forecasting sovereign defaults. It is our belief that through meticulous data analysis and innovative modeling, we can offer valuable tools for preempting and mitigating the impacts of fiscal crises on a global scale.

REFERENCES

[1] Marco Fioramanti. Predicting sovereign debt crises using artificial neural networks: A comparative approach. *Journal of Financial Stability*, 4(2):149–164, 2008.

[2] Grzegorz Mentel Beata Szetela and Jacek Brożyna. In search of insolvency among european countries. *Economic Research-Ekonomska Istraživanja*, 29(1):839–856, 2016.

[3] Sung Youl Oh, Jae Wook Song, Woojin Chang, and Minhyuk Lee. Estimation and forecasting of sovereign credit rating migration based on regime switching markov chain. *IEEE Access*, 7:115317–115330, 2019.

[4] Rani Wijayanti and Sagita Rachmanira. Early warning system for government debt crisis in developing countries. *Journal of Central Banking Theory and Practice*, 9(s1):103–124, 2020.

[5] David Alaminos, José Ignacio Peláez, M. Belén Salas, and Manuel A. Fernández-Gámez. Sovereign debt and currency crises prediction models using machine learning techniques. *Symmetry*, 13(4), 2021.

[6] Zhou Ming Matt and Wang Man Cang. Predictive Analysis of Fiscal Crises with Deep Learning Time Series Model. *International Journal of Economics and Finance*, 11(5):1–21, May 2019.