PREDICTING SOVEREIGN CREDIT EXPOSURE DURING POLITICAL TURMOIL: INSIGHTS FROM MACHINE LEARNING AND DEEP LEARNING MODELS

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# ABSTRACT

Sovereign credit risk has become increasingly significant for policymakers, investors, and financial institutions, particularly during periods of political instability. Traditional risk assessment methods often fail to capture the dynamic and nonlinear relationships in credit markets. This study explores the application of machine learning (ML) and deep learning (DL) techniques for forecasting sovereign credit risk under political crises. Using sovereign credit default swap (CDS) spreads and macroeconomic indicators from Egypt, Saudi Arabia, and Morocco, we implement models including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Extreme Gradient Boosting (XGBoost) to forecast default probability and CDS spread movements. Our results demonstrate that DL models, particularly GRU-based architectures, outperform traditional linear and classical statistical models in terms of predictive accuracy. The findings suggest that ML and DL approaches provide robust tools for capturing complex dependencies in sovereign credit risk, offering strategic insights for investors and policymakers facing political uncertainties.

**Keywords**: sovereign credit risk, political crisis, machine learning, deep learning, CDS spreads, LSTM, GRU

# INTRODUCTION

Sovereign credit risk represents the possibility that a government may fail to meet its debt obligations, either partially or fully, leading to significant repercussions for financial markets, investors, and overall economic stability. Governments issue sovereign debt to finance public spending, infrastructure projects, and social programs, and any disruption in the repayment of these obligations can trigger cascading effects across domestic and international financial systems (Abid & Abid, 2024 [2]; Augustin et al., 2022 [8]). The risk of default is particularly pronounced in emerging economies, where fiscal management, institutional strength, and political stability may vary considerably. Even in developed countries, political or economic shocks can result in sudden adjustments in sovereign credit risk perception, demonstrating the global interconnectedness of financial markets.

Political instability is a critical driver of sovereign credit risk. Factors such as regime changes, civil unrest, policy uncertainty, corruption, and geopolitical tensions can directly affect a government’s ability and willingness to service debt. Political crises can alter fiscal priorities, lead to unanticipated budget deficits, or disrupt trade and investment flows, ultimately raising the probability of default (Paret & Gilles, 2015 [75]; Badr & El Khadrawi, 2016 [7]). Historical evidence indicates that sovereign defaults and rating downgrades often follow periods of political turbulence. For example, sudden policy shifts or elections in certain emerging economies have historically led to sharp increases in sovereign CDS spreads, reflecting higher perceived default risk (Longstaff et al., 2011 [53]; Augustin et al., 2022 [8]).

Credit Default Swaps (CDSs) have emerged as essential market-based instruments for monitoring and quantifying sovereign credit risk. CDS spreads reflect the premium investors demand to hedge against the possibility of default, thus providing real-time insight into market perceptions of risk (Abid et al., 2020 [3]; Hull et al., 2004 [39]). Compared to traditional sovereign credit ratings, CDS spreads are more dynamic, reflecting immediate changes in investor sentiment, macroeconomic conditions, and geopolitical developments. Studies suggest that CDS markets are highly responsive to both domestic and international political events, making them particularly valuable for risk assessment during periods of political instability (Rodríguez et al., 2019 [77]; Naifar, 2020 [61]).

Forecasting sovereign credit risk, however, remains a complex task. Traditional models, such as regression-based approaches, Vector Autoregressions (VAR), and ARIMA models, primarily rely on historical trends and assume linear relationships among variables (Annaert et al., 2000 [5]; Cipollini & Missaglia, 2008 [17]). While these methods have proven useful under relatively stable market conditions, they often fail to capture sudden market reactions or nonlinear interactions during political crises. This limitation is particularly problematic when credit markets are subject to abrupt structural changes or regime shifts. For instance, sudden policy announcements, social unrest, or external shocks may generate nonlinear movements in CDS spreads that classical models cannot adequately predict (Shaw et al., 2014 [86]; Rodríguez et al., 2019 [77]).

Recent advancements in computational techniques have enabled the use of **machine learning (ML) and deep learning (DL)** for forecasting complex financial and economic time series. Unlike traditional models, ML and DL methods can automatically learn patterns from large datasets, identify hidden nonlinear relationships, and incorporate multiple temporal and cross-sectional features (Siami-Namini & Namin, 2018 [93]; Vukovic et al., 2022 [108]; Gao et al., 2017 [36]). Deep learning architectures, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), are specifically designed to handle sequential data and long-term dependencies, making them highly suitable for modeling CDS spreads and other financial time series (Chen et al., 2015 [19]; Bai et al., 2024 [9]; Wang et al., 2018 [110]). Additionally, ensemble methods such as XGBoost have demonstrated strong predictive capabilities in tabular datasets by combining decision trees in a gradient-boosting framework, allowing for robust handling of feature interactions and nonlinearities (Gogineni et al., 2024 [37]; Zhang & Jánošík, 2024 [113]).

In the context of sovereign credit risk, these computational approaches offer several advantages. First, ML and DL models can integrate heterogeneous data sources, including macroeconomic indicators, political risk indices, financial market data, and geopolitical news, providing a more comprehensive understanding of the factors driving risk (Abid & Abid, 2024 [2]; Ao & Fayek, 2023 [6]). Second, these models are capable of adaptive learning, which allows them to update predictions as new data becomes available, an essential feature in volatile environments. Third, deep learning architectures can detect subtle, nonlinear interactions

that traditional models often overlook, such as the delayed effects of fiscal policy changes or the amplification of political uncertainty across financial markets (Li et al., 2021 [51]; Vukovic et al., 2022 [108]).

This study focuses on forecasting sovereign credit risk under political turmoil using CDS market data and macroeconomic indicators from Egypt, Saudi Arabia, and Morocco. These countries were selected due to their diverse political landscapes, varying fiscal management practices, and exposure to both domestic and regional political crises (Abid & Abid, 2024 [2]; Barry, 2022 [15]; Boumahdi, 2022 [16]). The study integrates three advanced modeling frameworks: LSTM networks for capturing temporal dependencies, GRU networks for efficient sequence learning, and XGBoost for feature-rich tabular prediction. These models are compared with traditional statistical and linear approaches to assess relative performance.

The primary objectives of this study are threefold:

1. **To evaluate the predictive performance of machine learning and deep learning models**, including LSTM, GRU, and XGBoost, in forecasting sovereign credit risk during political crises. These models are assessed based on their ability to predict CDS spread movements and implied default probabilities.
2. **To compare these computational approaches against traditional statistical models**, including ARIMA, VAR, and linear regression, to determine the added value of ML/DL techniques in volatile and politically unstable environments.
3. **To provide insights into the influence of political events on sovereign credit risk and market behavior**, enabling policymakers, investors, and risk managers to better understand the dynamics of risk propagation and design appropriate mitigation strategies.

By addressing these objectives, the study contributes to the growing literature on the application of computational intelligence to financial risk management, highlighting the importance of integrating market-based and macroeconomic data in sovereign credit risk forecasting. Furthermore, the results offer practical guidance for investors and policymakers operating in politically sensitive regions, where traditional models may be insufficient for timely and accurate risk assessment (Rodríguez et al., 2019 [77]; Abid et al., 2020 [3]; Longstaff et al., 2011 [53]).

In summary, this research underscores the critical interplay between political instability, macroeconomic performance, and financial markets in shaping sovereign credit risk. By leveraging modern machine learning and deep learning techniques, it aims to develop robust predictive frameworks capable of anticipating market reactions and informing effective risk management decisions in uncertain political environments. The study demonstrates that advanced computational approaches can significantly enhance traditional risk assessment frameworks, providing timely, accurate, and actionable insights for a range of stakeholders.

**2. Literature Review**

**Sovereign Credit Risk and Political Crisis**

Sovereign credit risk reflects a government’s likelihood of default and is often captured via CDS spreads (Abid et al., 2020 [3]; Zhu, 2006 [117]). Political crises exacerbate risk through fiscal mismanagement, policy uncertainty, and investor panic (Barry, 2022 [15]; Boumahdi, 2022 [16]). Empirical studies show that sovereign CDS spreads are sensitive to political and macroeconomic shocks, indicating that political events

are leading indicators for market-based risk measures (Longstaff et al., 2011 [53]; Augustin et al., 2022 [8]; Naifar, 2020 [61]).

**Traditional Forecasting Methods**

Classical approaches, including dynamic factor models, ARIMA, and regression-based methods, have been used to forecast credit risk (Annaert et al., 2000 [5]; Cipollini & Missaglia, 2008 [17]; Li et al., 2021 [51]). While effective in stable periods, these methods often fail to capture nonlinear and temporal dependencies during crises (Shaw et al., 2014 [86]; Rodríguez et al., 2019 [77]).

**Machine Learning and Deep Learning in Financial Forecasting**

ML and DL techniques offer advantages in modeling complex financial systems, including nonlinearities, temporal sequences, and multivariate dependencies (Moscatelli et al., 2020 [62]; Kamath et al., 2024 [48]).

* **LSTM networks** are effective for sequence modeling and long-term dependencies in time series data (Chen et al., 2015 [19]; Cortez et al., 2018 [20]).
* **GRU networks** offer simplified architectures with fewer parameters, achieving comparable performance with lower computational cost (Bai et al., 2024 [9]; Wang et al., 2018 [110]).
* **Tree-based models**, such as XGBoost, have demonstrated strong predictive performance for tabular financial data (Gogineni et al., 2024 [37]; Zhang & Jánošík, 2024 [113]).

Several studies highlight the use of ML/DL in sovereign CDS forecasting. Li et al. (2021) [51] proposed a decomposition and reconstruction strategy using deep learning for China’s CDS markets. Vukovic et al. (2022) [108] demonstrated that ensemble ML/DL models outperform classical approaches during the COVID-19 pandemic.

**3. Methodology**

**Data Collection**

We collected daily sovereign CDS spreads, macroeconomic indicators (GDP, inflation, fiscal balance, foreign reserves), and political risk indices for Egypt, Saudi Arabia, and Morocco from 2015 to 2024 (Abid & Abid, 2024 [2]; Barry, 2022 [15]; Boumahdi, 2022 [16]). Political crises were identified using news datasets and official government reports.

**Model Development**

**Preprocessing**

Data were normalized, missing values imputed, and sequences generated for ML/DL input. Time lags were introduced to capture temporal dependencies (Siami-Namini & Namin, 2018 [93]; Ao & Fayek, 2023 [6]).

**Model Architectures**

* **LSTM:** Three-layer LSTM network with dropout regularization and ReLU activation, optimized using Adam optimizer (Chen et al., 2015 [19]; Cortez et al., 2018 [20]).
* **GRU:** Two-layer GRU network with sequence-to-one mapping for CDS spread prediction (Bai et al., 2024 [9]; Wang et al., 2018 [110]).
* **XGBoost:** Gradient-boosted decision trees with grid search hyperparameter tuning for tabular data (Gogineni et al., 2024 [37]; Zhang & Jánošík, 2024 [113]).

**Benchmark Models**

Traditional statistical methods, including ARIMA, VAR, and linear regression models, were implemented to benchmark performance (Li et al., 2021 [51]; Shaw et al., 2014 [86]).

**Evaluation Metrics**

Model performance was assessed using RMSE, MAE, and MAPE to capture prediction accuracy (Gao et al., 2017 [36]; Kamath et al., 2024 [48]).

**4. Results**

**Descriptive Statistics**

Table 1 presents descriptive statistics for CDS spreads and macroeconomic variables across the three countries. CDS spreads were significantly elevated during periods of political unrest, reflecting heightened sovereign credit risk (Abid & Abid, 2024 [2]; Barry, 2022 [15]).

**Model Performance**

DL models (LSTM, GRU) outperformed traditional benchmarks, with GRU showing the lowest RMSE and MAE across all three countries. XGBoost performed well for short-term CDS spread prediction, particularly when combined with macroeconomic features (Gogineni et al., 2024 [37])

| **Model** | **RMSE (Egypt)** | **RMSE (Saudi Arabia)** | **RMSE (Morocco)** |
| --- | --- | --- | --- |
| ARIMA | 12.35 | 10.87 | 9.56 |
| LSTM | 7.21 | 6.45 | 6.12 |
| GRU | 6.87 | 6.12 | 5.88 |
| XGBoost | 8.03 | 7.45 | 6.98 |

**Impact of Political Events**

Analysis shows that political crises induce abrupt CDS spread jumps, which GRU networks capture effectively due to their capacity for learning temporal dependencies (Abid & Suissi, 2024 [4]; Ao & Fayek, 2023 [6]).

**Robustness Checks**

Models were retrained using rolling windows, and the predictive superiority of GRU over LSTM and XGBoost remained consistent. Out-of-sample predictions maintained high accuracy even during crisis periods.

**5. Discussion**

The findings unequivocally demonstrate the **robust predictive power of Deep Learning (DL) models**, particularly **Gated Recurrent Unit (GRU) networks**, for forecasting **sovereign credit risk** during periods characterized by **political crises**. This success is rooted in their inherent ability to process and learn complex, time-dependent patterns, which is essential for capturing the swift and volatile market reactions to political instability.

The traditional methods, while historically foundational and useful under stable economic and political conditions, are shown to **fail** when faced with the sudden, non-linear market shifts precipitated by political events (Rodríguez et al., 2019 [77]; Longstaff et al., 2011 [53]). This deficiency stems from their structural limitations; traditional models are typically static or rely on assumptions of linear relationships that do not hold when political shocks disrupt fundamental economic expectations.

**Traditional Methods: Limitations in Volatile Conditions**

Traditional credit risk models—often based on structural models like Merton's, reduced-form models, or econometric techniques such as logit/probit regression—are built on the premise of relative market calm and predictability.

**1. Inability to Capture Non-Linearity**

Political events, such as unexpected elections, referendums, impeachments, civil unrest, or major policy shifts, introduce **tail risk** and **non-linear dependencies** into the market. A sudden announcement can cause an instantaneous, massive repricing of risk. Traditional models, designed for gradual changes, are **structurally incapable** of processing these sharp, discontinuous jumps in risk metrics. They typically rely on lagged economic variables and often fail to incorporate or appropriately weight high-frequency, qualitative (news-based) political data, which are the immediate drivers of crisis.

**2. Static Nature vs. Dynamic Reality**

Many classic models treat risk factors as relatively static or changing slowly. However, sovereign credit risk in a political crisis is intensely **dynamic**. The probability of default is constantly being reassessed by the market in real-time as new information emerges. This fast-moving, *sequence-dependent* nature of risk requires a model that can *remember* past states and use that memory to inform the prediction of the next state—a capability inherent to Recurrent Neural Networks (RNNs) and their variants like GRUs. The failure of traditional models in these conditions validates the need for a paradigm shift toward sequence modeling (Rodríguez et al., 2019 [77]).

**The Power of Sequence Modeling with GRU Networks**

The mechanism by which political instability elevates default probability is directly reflected in the market through metrics such as **Credit Default Swap (CDS) spreads**. CDS spreads represent the price of insuring against a sovereign default, making them a sensitive, forward-looking indicator of credit risk. When political uncertainty rises, the demand for this insurance increases, causing spreads to widen dramatically.

**Sequence modeling techniques** offered by Deep Learning, particularly the **GRU network**, are perfectly suited to forecast these dynamics (Abid et al., 2020 [3]; Abid & Abid, 2024 [2]).

**1. Gated Recurrent Units (GRUs) and Memory**

A GRU is a sophisticated type of RNN that employs "gates" (**update gate** and **reset gate**) to manage the flow of information through time. This design addresses the **vanishing gradient problem** common in simple RNNs, allowing the network to:

* **Selectively Remember**: The update gate determines how much of the past information (the previous hidden state) to carry forward to the current time step. This is crucial for maintaining long-term dependencies, such as the persistent effect of a constitutional crisis or a prolonged period of high debt.
* **Selectively Forget**: The reset gate determines how much of the past hidden state to forget. This allows the model to instantly discard irrelevant historical information when a major, new political shock requires a complete shift in risk assessment.

This superior memory management allows GRUs to effectively model the **sequence dependency** of sovereign credit risk. For example, a GRU can learn that the impact of a negative macroeconomic indicator is amplified when it follows a contentious election (a political crisis) compared to when it occurs during a stable administration.

**2. Enhanced Predictive Accuracy and Granularity**

The empirical results confirming the efficacy of ML and DL models underscore not only an **improvement in prediction accuracy** but also an **enhancement in the understanding of the dynamic interactions** between macroeconomic factors and sovereign credit markets.

Traditional models struggled to integrate a large volume of heterogeneous data (economic, political, sentiment data) effectively. DL models, especially when fed with both numerical macroeconomic time series and text-based political news/sentiment indices, can automatically **extract complex features** and latent relationships.

This enables a more granular understanding:

* **Interaction Effects**: The models reveal how political risk *modifies* the impact of macroeconomic variables. For instance, high debt () might be manageable in a stable country but becomes critically dangerous in a country facing imminent political fragmentation. The DL model learns and quantifies this **interaction effect**.
* **Leading Indicators**: By tracking the model's sensitivity to inputs, researchers can gain insight into which political and economic variables serve as the earliest and strongest **leading indicators** for CDS spread movements during a crisis.

**Implications for Risk Management and Policy**

The findings have profound implications for financial institutions, sovereign debt investors, and policymakers.

1. **Early Warning Systems**: The deployment of DL models, particularly GRUs, offers the potential for highly accurate **early warning systems** for sovereign default risk. This allows investors to hedge risk more effectively and regulators to prepare contingency plans.
2. **Stress Testing**: These advanced models provide a superior framework for **stress testing** sovereign portfolios under explicit and highly realistic political crisis scenarios, moving beyond simple, historically based macroeconomic shock tests.
3. **Policy Analysis**: For governments and international organizations (like the IMF or World Bank), the models offer a tool to quantify the **cost of political instability** in terms of increased borrowing costs (widened CDS spreads). This provides a quantitative impetus for prioritizing political stability and institutional strength alongside fiscal prudence.

**6. Conclusion**

This study applies ML and DL approaches to forecast sovereign credit risk under political crises. Key findings include:

1. GRU networks outperform LSTM, XGBoost, and traditional statistical models in CDS spread prediction.
2. Political crises significantly influence sovereign credit risk, which ML/DL models capture effectively.
3. Integration of macroeconomic indicators improves prediction accuracy, highlighting the importance of multi-source data in sovereign risk forecasting.

Future research could explore hybrid architectures combining DL with Bayesian networks, reinforcement learning, or graph-based models for real-time sovereign risk assessment (Robinson et al., 2010 [73]; Bai et al., 2024 [9]).

**References**

1. Abid, A., & Abid, F. (2023). A methodology to estimate the optimal debt ratio when asset returns, and default probability follow stochastic processes. Journal of Industrial & Management Optimization, 19(10), 1.
2. Abid, A., & Abid, F. (2024). Sovereign credit risk in Saudi Arabia, Morocco and Egypt. Journal of Risk and Financial Management, 17(7), 283.
3. Abid, A., Abid, F., & Kaffel, B. (2020). CDS-based implied probability of default estimation. The Journal of Risk Finance, 21(4), 399–422.
4. Abid, A., & Suissi, N. (2024). Sovereign CDS spread and term structure forecasting based on neural network. Global Business Review.
5. Annaert, J., De Ceuster, M., & De Jonghe, F. (2000). Modelling European credit spreads. Deloitte & Touche.
6. Ao, S. I., & Fayek, H. (2023). Continual deep learning for time series modeling. Sensors, 23(16), 7167.
7. Badr, O. M., & El khadrawi, A. F. (2016). Macroeconomic variables, government effectiveness and sovereign credit rating: A case of Egypt. Applied Economics and Finance, 3(4), 29–36.
8. Augustin, P., Sokolovski, V., Subrahmanyam, M. G., & Tomio, D. (2022). How sovereign is sovereign credit risk? Global prices, local quantities. Journal of Monetary Economics, 131, 92–111.
9. Bai, M., Zhou, Z., Li, J., Chen, Y., Liu, J., Zhao, X., & Yu, D. (2024). Deep graph gated recurrent unit network-based spatial–temporal multi-task learning for intelligent information fusion of multiple sites. Expert Systems with Applications, 240, 122072.