ENHANCING CRISIS PREDICTION: A DEEP LEARNING APPROACH USING LSTM WITH CDS AND BOND SPREADS

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Abstract

This study proposes an innovative approach to financial crisis prediction by employing Long Short-Term Memory (LSTM) deep learning techniques. The research analyzes Turkey's credit default swaps (CDS) and the bond yield spreads relative to German Bunds over the period 2010–2024, determining crisis threshold values using the Logistic Smooth Transition Autoregressive (LSTAR) model. The LSTM network predicts crisis probabilities with an accuracy rate of 78%. The model successfully identifies regime shifts by detecting a critical threshold value of 522.28 in CDS spreads. The findings demonstrate the superiority of deep learning methods over traditional econometric approaches in forecasting financial crises and contribute to the development of early warning systems for policymakers.

Keywords: Financial crisis prediction, LSTM, deep learning, CDS, bond spread, crisis probability

JEL Classification: G01, C53, C45, E44, C22, E32, G15

Özet

Bu çalışma, finansal kriz tahmininde Long Short-Term Memory (LSTM) derin öğrenme tekniklerini kullanarak yenilikçi bir yaklaşım sunmaktadır. Araştırmada, Türkiye'nin kredi temerrüt swapları (CDS) ve Almanya ile olan tahvil getiri farkları 2010-2024 döneminde analiz edilerek, Logistic Smooth Transition Autoregressive (LSTAR) modeliyle kriz eşik değerleri belirlenmiştir. LSTM ağı, %78 doğruluk oranıyla kriz olasılıklarını tahmin etmektedir. Model, CDS primlerinde 522.28 kritik eşik değerini tespit ederek rejim değişikliklerini başarıyla yakalamıştır. Sonuçlar, geleneksel ekonometrik yöntemlere kıyasla derin öğrenme tekniklerinin finansal kriz öngörüsündeki üstünlüğünü göstermekte ve politika yapıcılar için erken uyarı sistemlerinin geliştirilmesine katkı sağlamaktadır.

Anahtar Kelimeler: Finansal kriz tahmini, LSTM, derin öğrenme, CDS, tahvil getirisi farkı, kriz olasılığı

JEL Sınıflandırması: G01, C53, C45, E44, C22, E32, G15

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1. Introduction

The financial crises of the past few decades, including the 2008 Global Financial Crisis, have emphasized the need for early warning systems that can identify the emergence of market instability. Anticipating such crises is inherently difficult because of the intricate, non-linear, and constantly changing characteristics of financial markets. Traditional econometric models, while useful, frequently struggle to reflect the complex relationships between macroeconomic variables and market fluctuations, sespecially during times of increased volatility. This challenge partly drives the emphasis on non-linear modeling techniques and mathematical statistical methods in research related to macroeconomics and financial econometrics.

Recent advancements in artificial intelligence and machine learning have opened new avenues to tackle these challenges. Deep learning, especially Long Short-Term Memory (LSTM) networks, has demonstrated remarkable efficacy in predicting sequential data because of their ability to maintain long-term dependencies and manage data sequences with differing time intervals. In this study, LSTM networks are employed to assess the probability of financial crises. Sovereign Credit Default Swaps (CDS) and bond yield spreads, serving as essential indicators, are included as input variables in the LSTM model.

1.1. The Function of Credit Default Swaps in Assessing Credit Risk and Economic Evaluations

Credit Default Swaps (CDS) play a crucial role in academic research as they offer valuable perspectives on perceived credit risk. CDS pricing reflects market perceptions and expectations regarding creditworthiness, functioning as financial instruments akin to insurance against defaults. From a research perspective, CDS data provides critical insights into credit risk behaviors, valuation methodologies, and the relationships between credit markets and overall financial stability. By examining CDS spreads, researchers can assess the risk levels associated with various entities, investigate how economic and financial changes influence credit risk perceptions, and contribute to the development of models that enhance our understanding of financial resilience and systemic risks. As a result, CDS spreads have emerged as a fundamental metric for evaluating economic conditions across countries.

The innovation of this study lies in integrating CDS and bond spread data into a deep learning framework with a sigmoid activation function to predict future crisis probabilities. Moreover, this study is particularly significant for examining the bond spread between Germany and Turkey as a measure of sovereign risk and integrating it with CDS spreads to reflect market perceptions regarding defaults within the model. The methodology applied in this paper offers a dynamic, data-driven strategy for forecasting financial crises and is believed to have the potential to surpass traditional econometric techniques.

The conceptual basis of financial turmoil, particularly the significance of CDS and sovereign risk differentials, has been widely examined in previous research. Reinhart and Rogoff (2009) argued that economic disruptions are frequently initiated by substantial declines in fundamental macroeconomic indicators. In this analysis, CDS differentials are chosen as key metrics for identifying financial distress due to their capacity to capture investor risk sentiment. Moreover, sovereign debt differentials facilitate a comparative evaluation of risk perceptions across nations. Nonetheless, additional variables, such as leverage ratios, are also essential in such assessments and are planned to be incorporated into the framework in subsequent investigations.

2. Literature Review

The prediction of financial crises has been extensively studied in the fields of economics and finance, with a variety of models developed to anticipate market downturns. Early works, such as Kaminsky, Lizondo, and Reinhart (1998), utilized macroeconomic indicators to identify vulnerabilities that could lead to crises. However, the static nature of these models limited their ability to capture the rapidly changing dynamics of modern financial markets.

Another study that is likely to attract attention in terms of addressing CDS spreads is the one conducted by Norden and Weber (2009). The study provides a significant empirical analysis of the co-movement dynamics between credit default swaps (CDS), bond, and stock markets. The research by Norden and Weber reveals that stock returns lead changes in CDS and bond spreads, a finding that contributes to a deeper understanding of the evolving relationships between these markets. Additionally, it demonstrates that the CDS market is more sensitive to the stock market than to the bond market, and that CDS plays a larger role in price discovery compared to the bond market. This study builds on these findings by integrating both government bond spreads and CDS spreads into a unified LSTM framework, offering a more comprehensive perspective on market risk.

In the context of financial crisis prediction, bond spreads and CDS spreads are recognized as leading indicators of sovereign risk. Delatte et al. (2012) analyzed bond spreads to assess the risk of sovereign default.

With the rise of machine learning, researchers started integrating advanced algorithms to forecast financial instability. Sun and Li (2012) employed support vector machines (SVM) for predicting financial distress, achieving enhanced accuracy over conventional approaches. In recent years, the advent of deep learning techniques has revolutionized this area, with LSTM networks gaining special recognition for their ability to handle time-series predictions. For example, Bao et al. (2017) showed that LSTM could surpass other neural networks in predicting stock market movements. Their work serves as an important reference, showcasing the effectiveness of deep learning techniques in forecasting financial time series. In particular, their framework combining wavelet transforms (WT), stacked autoencoders (SAEs), and long short-term memory (LSTM) networks provides an innovative method for reducing noise in financial data and extracting significant features. The study illustrates that deep learning models perform better than traditional methods in capturing the intricate nature of financial markets.

Fischer and Krauss (2017) demonstrated the success of LSTM in predicting the direction of S&P 500 stocks by comparing its accuracy with other classification models.

Althelaya et al. (2018) examined the success of bidirectional and stacked LSTM architectures in forecasting financial time series.

Chatzis et al. (2018) developed a forecasting mechanism for stock market crises by examining the transmission channels of crash events across international stock, bond, and currency markets, using various machine learning algorithms, including deep learning and boosting techniques. With data from 39 countries, their model identified key variables associated with returns and volatility and adjusted for data imbalance using bootstrap sampling. The results indicate strong persistence and interdependence of crises across markets, with deep neural networks significantly enhancing classification accuracy, thereby contributing to the development of a risk-sensitive global early warning system for financial stability.

Egami and Kevkhishvili (2019) stated in their study that CDS spread fluctuations provide forecasting during crisis periods and offered valuable insights into the CDS-bond spread relationship.

Ye et al. (2020) analyze 128 defaults among U.S. CDS reference entities from 2001 to 2020 and find that the five-year CDS spread is a significant predictor of corporate default. The results hold for both financial and non-financial firms, across various time horizons (up to 12 months) and market conditions, including the Great Financial Crisis. The study further reveals that the predictive power of the CDS spread primarily stems from its physical default component, which is confirmed by both in-sample and out-of-sample data. This highlights the importance of CDS pricing information in predicting corporate defaults.

Bukhari et al. (2020) introduced a novel hybrid approach combining ARFIMA and LSTM to address the limitations of traditional techniques in predicting the volatility and unpredictability of stock markets. By leveraging ARFIMA's long-memory traits, the model effectively filters linear trends, while non-linear elements are analyzed via the LSTM network.

Liu and Long (2020) proposed an advanced stock closing price prediction framework that outshines conventional methods. This framework includes data preprocessing through empirical wavelet transform (EWT) and post-processing with an outlier-robust extreme learning machine (ORELM). Additionally, the LSTM network predictor is refined using dropout techniques and particle swarm optimization (PSO). Experimental findings show that this hybrid model achieves top-tier accuracy, making it well-suited for stock market oversight and financial data analysis.

Kamdem et al. (2020) applied the Long Short-Term Memory (LSTM) deep learning model to forecast commodity prices, specifically crude oil prices, with high precision. The study analyzed how the coronavirus affected commodity price fluctuations using correlation and Granger causality methods, revealing that the pandemic influences prices through the number of confirmed cases and fatalities. Furthermore, a hybrid ARIMA-Wavelet model was used to predict COVID-19's spread, underscoring a strong causal link between the pandemic and commodity prices, suggesting that forecasting COVID-19's trajectory could assist in anticipating future price trends.

Zhang et al. (2020) proposed a new hybrid model, CEEMD-PCA-LSTM, for stock market prediction. In this model, complementary ensemble empirical mode decomposition (CEEMD) is used to decompose time series into intrinsic mode functions (IMFs), while principal component analysis (PCA) is applied for dimensionality reduction, improving prediction speed and accuracy. The decomposed components are then fed into LSTM networks to predict the next day's closing price. The empirical results from six stock indices demonstrate that the proposed model outperforms benchmark models in terms of prediction accuracy and robustness.

Jung and Choi (2021) focused on forecasting foreign exchange (FX) volatility using deep learning models and proposed a hybrid model that combines Long Short-Term Memory (LSTM) and autoencoder techniques. The proposed model was applied to Foreign Exchange Volatility Index (FXVIX) data, particularly from 2010 to 2019. The results demonstrated that the proposed autoencoder-LSTM model outperformed the traditional LSTM model in predicting FX volatility.

Prasetyo and Rokhim (2022) carried out research on utilizing LSTM to forecast the Indonesian stock market amid COVID-19. In their study, they implemented the BiLSTM model to project stock prices within Indonesia's financial sector during the COVID-19 period, focusing on historical records from a specific firm. The model was assessed using MAPE and SMAPE metrics, showing minimal error in price forecasting. Intervention analysis indicated that the health sector saw positive outcomes, whereas sectors like transportation, finance, IT, and entertainment faced negative effects. Their findings offer valuable insights for investors regarding sector-specific impacts and possible investment tactics during financial crises.

Widiputra and Juwono (2024) evaluate deep learning models (CNN, LSTM, Stacked-LSTM, CNN-LSTM, and ConvLSTM) for predicting financial time series in their study, focusing on the impact of model architecture and data properties on prediction accuracy. Using daily data from four Asian stock indices during the early phase of the COVID-19 pandemic, their analysis reveals that no single model consistently outperforms others across all scenarios. The results indicate that standalone models perform better with more stable data, while hybrid models are more effective for chaotic time series.

Studies on the crisis risk of the Turkish economy are limited in number. A significant proportion of these studies have employed the "Signal Approach." The signal approach was developed by Kaminsky, Lizondo, and Reinhart (1998). The studies by Cicioğlu and Yıldız (2018) and Karaçor and Alptekin (2006) are also examples of research analyzing crises using the signal approach. This method provides a model that signals potential crises when macroeconomic indicators exceed certain thresholds. For instance, Kaya and Yılmaz (2006) analyzed the Turkish economy for the 1990–2002 period and identified the public sector borrowing requirement-to-GDP ratio as the best-performing variable.

Compared to the study by Kaya and Yılmaz (2006), which utilizes the signal approach, this research introduces several important innovations. While Kaya and Yılmaz (2006) focused on the 1990:01–2002:12 period, this study analyzes the more recent period of 2010:01–2024:09, thus incorporating the effects of contemporary global events. This makes the dataset more relevant to current dynamics.

Methodologically, while the signal approach relies on traditional statistical methods, this research integrates modern deep learning techniques, such as Long Short-Term Memory (LSTM) networks, to develop an advanced crisis forecasting model. LSTM stands out for its ability to analyze complex time-series data, offering higher accuracy in crisis prediction compared to the signal approach. Furthermore, this study incorporates a model that uses the sigmoid activation function and statistically defined threshold values to determine crisis probabilities. Instead of relying on simple statistical methods to identify thresholds, the Logistic

Smooth Transition Autoregressive (LSTAR) model was employed to define regime shifts, adding robustness to the analysis.

Another innovation of this study lies in its selection of variables. Unlike the traditional use of macroeconomic indicators, this research focuses on bond yield spreads, highlighting their performance relative to the country in question and their sensitivity to global risk positions. Analogically, just as a country's integration with global value chains is critical, the quality of bond market spreads is equally significant. Additionally, the inclusion of Credit Default Swap (CDS) prices a key variable in recent academic and policy discourse further enhances the sensitivity and precision of the model. CDS spreads, recognized for their critical role in representing financial distress, distinguish this study from its predecessors in the literature.

3. Methodology

3.1 Data and Preprocessing

In this study, the bond spreads between Germany and Turkey's sovereign bond yields and Turkey's Credit Default Swap (CDS) prices are analyzed to model and forecast financial stress. The bond spread is defined as the differential between the 10-year sovereign bond yield of Turkey and that of Germany. This spread serves as a key indicator of relative risk perception between the two countries, with Germany's yield often used as a benchmark for financial stability within the Eurozone. Concurrently, the CDS spreads provide a direct market-based assessment of Turkey's default risk, representing the cost of insuring against the possibility of sovereign default.

The dataset spans a broad period from January 2010 (31.01.2010) to September 2024 (09.09.2024) and includes 763 weekly observations. This timeframe potentially captures residual effects of the global financial crisis that began in the summer of 2007, as well as significant global and regional financial events such as the European sovereign debt crisis and the COVID-19 pandemic. By encompassing these periods, the dataset enables the analysis of dynamic shifts in risk perceptions during phases of financial turbulence and recovery. The data was obtained from publicly available financial databases to ensure transparency and reproducibility of the analysis.

In the preparation phase for model training, the MinMaxScaler has been applied to normalize all input features, including bond spreads and CDS spreads. This scaling process transforms the data into a consistent range between 0 and 1, which is crucial for deep learning algorithms such as Long Short-Term Memory (LSTM) networks. Normalization not only prevents any single feature from dominating the learning process due to its scale but also accelerates the convergence of the neural network, leading to more efficient and stable training. By standardizing the input data, potential issues related to varying scales are mitigated, ensuring that the model focuses on learning the underlying patterns in the time series rather than being influenced by disparate data magnitudes.

This methodological approach lays the foundation for constructing a robust LSTM-based predictive model capable of capturing the complex temporal dependencies within the bond and CDS markets, thereby providing a sophisticated tool for forecasting sovereign risk and financial instability. Through this analysis, the aim is to offer deeper insights into the interplay between sovereign bond markets and CDS pricing, contributing to the broader literature on financial crisis prediction and risk management in emerging markets.

The selection of CDS spreads and sovereign bond yield differentials as the sole input variables in this study is grounded in several methodological and empirical considerations. First, both indicators are market-based measures that reflect real-time investor risk perceptions, offering a forward-looking assessment of sovereign creditworthiness that macroeconomic aggregates typically released with considerable lags cannot provide (Delatte et al., 2012). Second, CDS spreads and bond yield differentials have been extensively validated in the literature as leading indicators of sovereign distress (Reinhart & Rogoff, 2009; Norden & Weber, 2009), and their joint inclusion captures both the absolute level of default risk and the relative risk perception vis-à-vis a benchmark economy. Third, limiting the input space to two highly informative variables mitigates the risk of overfitting in the LSTM architecture, which is particularly relevant given the moderate sample size of 763 weekly observations. It is acknowledged that traditional early warning systems frequently incorporate additional macroeconomic indicators such as exchange rate volatility, foreign reserve adequacy, and current account balances (Kaminsky et al., 1998). The exclusion of these variables constitutes a deliberate methodological choice aimed at maintaining model parsimony and focusing on high-frequency, market-based signals. Future research may extend the proposed framework by incorporating such macroeconomic variables to evaluate whether they provide incremental predictive power beyond the market-based indicators employed herein.

3.2 CDS Regime Shift as a Crisis Indicator through LSTAR Regime-Switching Modeling

The LSTAR (Logistic Smooth Transition Autoregressive) model is a powerful approach for capturing nonlinear regime changes in time series data. This model explores how the behavior of a time series varies around a designated threshold and reveals the inclination of the series to shift between distinct regimes. The LSTAR model is especially suited for analyzing how certain macroeconomic or financial indicators perform across varying economic conditions. Its defining feature is the presumption that regime shifts occur gradually rather than abruptly, allowing for a smoother transition that better reflects the inherent uncertainty and fluctuations in financial markets, producing results more aligned with real-world data.

In this research, when the LSTAR model is applied to CDS spreads, the hypothesis is centered on the idea that surpassing a particular threshold value triggers nonlinear transition dynamics in the series, potentially serving as an early warning of an impending financial crisis. Within this context, the LSTAR model's role in pinpointing threshold values is assessed as a mathematical tool for identifying regime changes in financial series, effectively capturing perceptions of market risk.

The LSTAR analysis incorporates a self-exciting model structure, utilizing the lagged values of the CDS price as the exogenous factor. The threshold level identified through the LSTAR framework not only signals a shift in statistical behavior but also indicates that the CDS threshold, seen as a warning in macroeconomic terms, has been breached in a potentially adverse manner. Therefore, this threshold, which prompts a regime change, will be interpreted not only as a technical boundary but also as a key indicator that influences market crisis perceptions and thus shapes risk management strategies. This study, where the probability of a crisis is derived as a concrete result, also addresses the conditions under which an economic crisis may be defined within this evaluative framework.

Furthermore, the threshold found in CDS spreads is viewed as essential not only for identifying past economic disruptions but also for anticipating possible future crises.

3.2.1. LSTAR Modeling Structure

The LSTAR (Logistic Smooth Transition Autoregressive) model is designed to capture nonlinear dynamics in time series by modeling regime shifts through a smooth transition between different states. This model is particularly effective in identifying non-linear patterns in financial time series data. The general mathematical formulation of the LSTAR model can be expressed as follows:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \left(\theta_0 + \sum_{i=1}^{p} \theta_i y_{t-i} \right) G(s_{t-d}; \gamma, c) + \varepsilon_t \qquad (1)$$

Where:

y_t represents the dependent variable at time t (e.g., CDS spreads).

ϕ_0 , ϕ_i are the coefficients in the first regime.

θ_0 , θ_i are the coefficients in the second regime.

p denotes the lag order of the model.

ε_t is the error term, with $\varepsilon_t \sim N(0,\sigma^2)$.

$G(s_{t-d};\gamma,c)$ is the transition function that facilitates the switching between regimes based on the lagged values of the independent variable.

Transition Function

The transition function in the LSTAR model allows for a smooth shift between different regimes and is defined as follows:

$$G(s_{t-d};\gamma,c) = \frac{1}{1+\exp(-\gamma(s_{t-d}-c)} \tag{2}$$

Where:

s_{t-d} is the transition variable, typically represented by the lagged value of the dependent variable (e.g., y_{t-d}).

$\gamma > 0$ is the parameter that controls the speed of transition. A larger γ value indicates a sharper transition between regimes.

c is the threshold or center value of the transition variable s_{t-d} .

The transition function $G(s_{t-d};\gamma,c)$ takes values between 0 and 1. When $s_{t-d} = c$, the function equals 0.5, indicating that both regimes have equal influence.

3.3. Rationale for Selecting LSTM and Its Advantages Over Other Algorithms

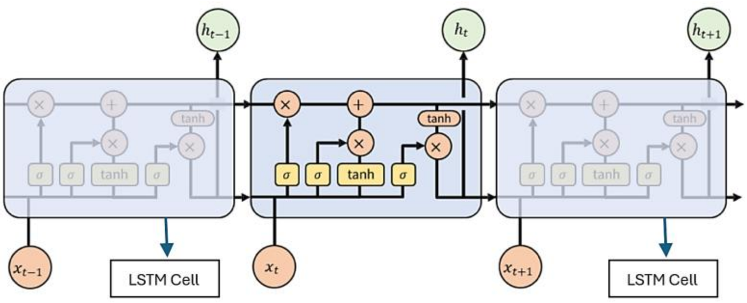
The fundamental justification for selecting Long Short-Term Memory (LSTM) networks for financial time series prediction lies in their capability to efficiently recognize intricate and prolonged dependencies. Temporal data frequently exhibit nonlinear characteristics, irregular fluctuations, and patterns emerging at various time horizons. Due to its distinctive control mechanisms, LSTM is specifically structured to handle these complexities. Notably, components such as the forget gate, which allows the system to disregard extraneous prior details, and the cell state, which retains crucial information, render LSTM considerably more effective than conventional techniques and alternative computational models.

LSTM frameworks provide multiple notable benefits over standard predictive algorithms in financial time series estimation. Conventional techniques like Stochastic Gradient Machine (SGM) and Random Forest (RF) are proficient in identifying short-term relationships but encounter difficulties in capturing extended temporal linkages. LSTM maintains historical details, making it particularly advantageous for modeling gradual, accumulative fluctuations in CDS valuations and debt differentials, both of which are essential elements in financial distress scenarios. Additionally, financial time series often follow nonlinear trajectories, and unlike decision trees and other non-deep learning approaches, LSTM adeptly processes these intricacies through its tanh and sigmoid transformation functions.

Another major strength of LSTM is its inherent ability to handle ordered data sequences, removing the necessity for extensive attribute engineering required by approaches such as RF and SGM, thereby boosting predictive accuracy. Furthermore, LSTM swiftly adjusts to abrupt market fluctuations, such as steep surges in CDS valuations or sudden variations in debt differentials, enhancing the reliability of crisis identification. Empirical investigations (e.g., Bao et al., 2017; Fischer & Krauss, 2017) have illustrated that LSTM surpasses SVMs and decision trees in financial prediction, particularly regarding precision, recall, and F1-score. Additionally, LSTM seamlessly incorporates multiple financial indicators, such as CDS valuations and debt differentials, emphasizing its versatility in sophisticated financial assessments. These advantages establish LSTM as a resilient instrument for financial time series estimation, validating its exclusive implementation in this research without necessitating direct evaluations against alternative methodologies. LSTM's proficiency in capturing extended dependencies, its adaptability to nonlinear structures, and its intrinsic processing of sequential data constitute the principal factors behind its selection in this study.

3.3.1. LSTM Model Architecture

Figure 1. LSTM Model Framework



Source: Author

LSTM (Long Short-Term Memory) networks are a type of recurrent neural network (RNN) designed to analyze time series data and capture long-term dependencies in sequential data. The mathematical structure of LSTMs includes specialized gates that are designed to retain important information over time steps and forget irrelevant information. To understand LSTMs, it is essential to examine their key components, namely the input, forget, and output gates.

$$f_t = \sigma\,(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

Model (3) represents the output value of the forget gate. In this model, σ is the sigmoid activation function, which returns a value between 0 and 1. Additionally, W_f denotes the learnable weight matrix, h_{t-1} represents the hidden state from the previous time step, x_t is the input at the current time step, and b_f refers to the bias term of the forget gate.

The input gate, which controls how much new information is added to the cell state, is represented in two stages. One is the 'Sigmoid Gate,' which determines which information will be updated, and the other is the 'tanh layer,' which represents the new information to be added to the cell. This can be mathematically expressed in Model (4) and Model (5).

$$i_t = \sigma\,(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

Here, i_t is the output of the input gate, and $\tilde{C}_t$ represents the new candidate cell state. W_i and W_C are the learnable weight matrices, while b_i and b_C are the bias terms.

The output gate, which determines which information will be transferred to the next hidden state based on the cell state, is defined by Model (6) below.

$$o_t = \sigma\,(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

The subsequent output is determined by the mathematical expression in Model (7).

$$h_t = o_t . \tanh(C_t) \tag{7}$$

Here, o_t represents the output of the output gate, h_t denotes the hidden state at the current time step, and C_t refers to the updated cell state. The cell state is updated as shown in Model (8).

$$C_t = f_t . C_{t-1} + i_t . \tilde{C}_t \tag{8}$$

According to Model (8), the forget gate determines how much of the previous cell state will be retained, while the input gate determines how much of the new information will be added to the cell state.

The general flow of an LSTM involves the forget gate determining which information from the previous cell state should be discarded, the input gate adding new information to the cell state, and the output gate calculating the hidden state based on the updated cell state. This structure enables LSTMs to effectively learn long-term dependencies in time series data.

This study presents the design and implementation of an advanced Long Short-Term Memory (LSTM) network specifically tailored to predict the likelihood of financial crises. The model is structured as a two-layer LSTM network optimized for sequential time-series data that captures the temporal dependencies inherent in financial markets. The choice of LSTM architecture is motivated by its ability to efficiently model long-term dependencies and its proven effectiveness in handling non-linear patterns, which are characteristic of financial crises and their precursors.

The input to the model is composed of time-ordered financial data over a 60-day look-back window, incorporating both Credit Default Swap (CDS) prices and bond yield spreads. The 60-day time horizon was selected based on the need to capture both short- and medium-term market fluctuations, which are critical for understanding the evolving nature of financial stress. The inclusion of bond spreads reflects the relative risk perception between sovereign issuers, while CDS spreads provide a direct, market-based measure of default risk. By integrating these two key financial indicators, the model aims to capture a more comprehensive view of sovereign risk.

The model output is a binary classification designed to predict the likelihood of a financial crisis, indicating whether a crisis is probable (denoted as 1) or unlikely (denoted as 0). The crisis classification is based on a threshold determined through LSTAR analysis of CDS spreads; this level signifies an increased default risk and triggers regime shifts in the statistical structure of the CDS variable. As a result of this assessment, the binary output representing the likelihood or unlikelihood of a crisis aligns with the practical requirements of risk management frameworks, which necessitate timely intervention and mitigation strategies for early crisis detection.

Building upon the aforementioned motivations, the details regarding the use of LSTM modeling to obtain the core framework of crisis probabilities in this study are categorized and explained as follows.

3.3.2. Data Scaling and Feature Engineering

To optimize model performance, the CDS spreads and bond spread data were scaled to the [0, 1] range. This scaling process was performed using the MinMaxScaler, ensuring that the differently scaled variables in the dataset could be processed more effectively by the model.

3.3.3. Time Series Data Preparation

To enable the Long Short-Term Memory (LSTM) model to effectively process time series data, sequences based on 60 weeks of historical data were created. Each sequence was labeled to predict the crisis probability for the upcoming week. A crisis condition was defined as the CDS price exceeding the regime-switching value (or threshold) determined by the LSTAR analysis. Specifically, the threshold value of 522.28 identified by the LSTAR model was used to construct a binary target variable: for any given week, if the CDS spread exceeded this threshold, the target was coded as y=1 (crisis); otherwise, it was coded as y=0 (no crisis). This binary label served as the dependent variable in the supervised learning framework. It should be noted that the LSTAR output was not fed into the LSTM as a continuous probability or as a direct input feature; rather, the LSTAR model's contribution was limited to determining the crisis threshold, which was then applied to generate binary labels for the entire sample period. This two-stage approach where LSTAR identifies the regime-switching threshold and LSTM learns the temporal patterns leading to threshold exceedances ensures methodological transparency and reproducibility. This labeling provides an important classification criterion for the early detection of financial crises.

3.3.4. Model Development and Training

During the model development process, a two-layered LSTM network was constructed using the Keras library. To mitigate the risk of overfitting, a 20% dropout rate was applied after each LSTM layer, and L2 regularization was integrated. The model was compiled using the binary cross-entropy loss function and the Adam optimization algorithm. In the training process, the dataset was split into 80% training and 20% testing while preserving the time series nature of the data. Additionally, 20% of the training data was allocated for validation purposes. The model was trained for 100 epochs with a batch size of 64. This configuration enhances both the learning capacity of the model and its ability to generalize to unseen data.

3.3.5. Prediction and Forward-Looking Analysis

Once the training phase was finished, the model was employed to forecast the probability of financial crises for the next 10 periods. In this method, the latest 60 weeks of normalized data were utilized, with new predictions incorporated at every step. The bond spread value was not constant throughout the forecast; instead, it was modified based on the crisis likelihood estimated by the model, allowing the bond spread to vary dynamically in line with the projected CDS values. At each stage, the model predicted the likelihood of a crisis according to the current data sequence, and this prediction was included in the dataset for the subsequent period.

The outlined iterative prediction framework enables the evaluation of possible crisis developments by considering the impacts of existing market conditions. The model integrates current information that reflects the fluctuations and uncertainties present in financial markets, providing a renewed viewpoint with every forecast that utilizes historical data. Consequently, a deeper insight into the possible future crisis trajectory is obtained.

This approach is essential for predicting and maintaining financial stability, providing important insights into the model's practical application. Moreover, the dynamic forecasting method described in this research equips market players and policymakers with vital resources to assess potential risks quickly.

4. Findings

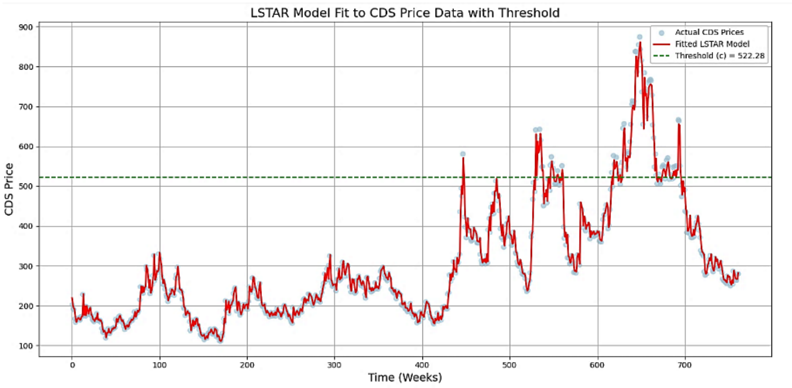
4.1. Regime shifts in CDS pricing

In our study, the Logistic Smooth Transition Autoregressive (LSTAR) model was applied to capture the nonlinear self-exciting dynamics of the Credit Default Swap (CDS) price variable. This method allows for dynamic transitions between different regimes of market behavior, as reflected by changes in CDS spreads. The CDS data were transformed using a logistic transition function, scaled, and optimized with a threshold determined by the data itself.

During the estimation process, the initial parameter values were refined using the L-BFGS-B optimization method. The estimated parameters included $\phi_0 = 0.0136$, $\phi_1 = 1.013$, $\phi_0 = -0.073$, $\phi_1 = -0.0203$ and the transition parameter $\gamma = 5629.52$. Most notably, the scaled threshold parameter c_{scaled} was found to be 1.42, corresponding to an original threshold of $c_{orginal}$=522.28 in the CDS price series. Consistent with the smooth transition nature of the LSTAR model, this value represents the transition center point (c) of the logistic transition function, around which market dynamics gradually shift between low-risk and high-risk regimes. The speed of this transition is governed by the γ parameter, meaning that the threshold should be interpreted not as a sharp binary boundary but as the midpoint of a smooth regime shift.

Figure 2. shows that the predicted and actual values for the CDS variable are closely aligned, confirming the model's effectiveness in capturing the nonlinear dynamics of CDS spreads. Furthermore, the identified threshold of 522.28 represents the center of a smooth transition zone where financial regime shifts occur. Rather than constituting an abrupt structural break, this value denotes the point at which the logistic transition function equals 0.5, indicating that both regimes exert equal influence. When CDS spreads exceed this threshold, it signals that markets may be entering a heightened risk environment, potentially indicating financial instability.

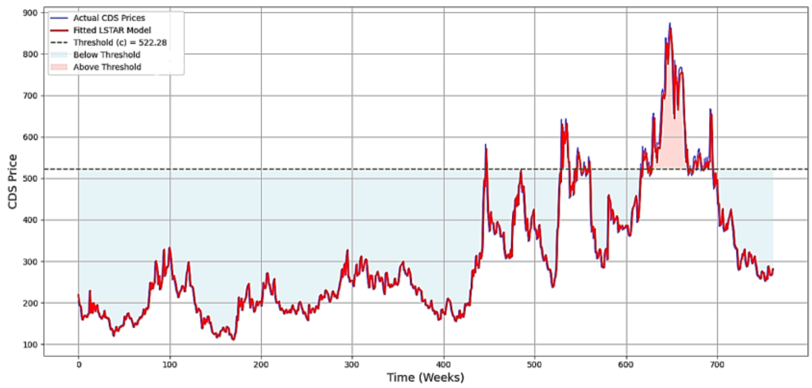
Figure 2. LSTAR Model Fit to CDS Price Data with Threshold



Source: Author

In Figure 3, the data regions corresponding to the regimes above and below the threshold value are illustrated. This figure represents the transition from the regime that accounts for a significant portion of the observations (Low regime: 0.8871) to the other regime (High regime: 0.1129). It highlights that high CDS spreads, associated with the high regime and relatively fewer data points, correspond to a crisis scenario.

Figure 3. LSTAR Model Fit to CDS Price Data with Regimes



Source: Author

However, some fluctuations in the transition function were observed, particularly during extreme movements in CDS spreads. This sensitivity suggests that further fine-tuning of model parameters, such as the transition speed, γ, and incorporating additional financial indicators could improve the accuracy and stability of the forecasts.

Methodologically, the LSTAR model contributes to this study by addressing the nonlinear regime-switching dynamics in CDS spreads. By identifying regime changes and critical threshold points, the model offers policymakers and investors a powerful tool for forecasting financial crises, thereby facilitating more informed decision-making and timely interventions. In summary, the unique role of the LSTAR model in this study lies in its ability to detect the crisis signal threshold that triggers a regime shift in CDS spreads, thus helping to estimate the likelihood of financial crises.

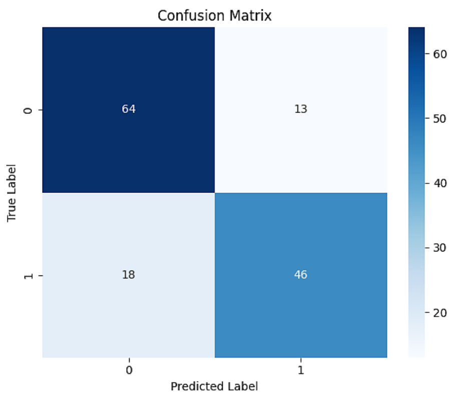
4.2. Optimization of the LSTM Model

In the methodological second phase of this study, a Long Short-Term Memory (LSTM) neural network was implemented to dynamically predict financial crises utilizing CDS spreads and bond spreads.

The LSTM model, trained over 100 epochs, effectively learned patterns from 60 weeks of historical data, achieving nearly 100% training accuracy and approximately 78% validation accuracy. The gap between training and validation accuracy warrants careful examination with respect to potential overfitting. Several regularization strategies were implemented to address this concern. First, a 20% dropout rate was applied after each LSTM layer to prevent co-adaptation of neurons. Second, L2 regularization was integrated into the network weights to penalize excessive parameter magnitudes. Third, the Early Stopping mechanism was employed, halting the training once the validation loss plateaued, ensuring that the best model weights were preserved. Despite these measures, the residual gap between training and validation performance can be attributed to the inherent characteristics of the CDS price series, which exhibits high volatility and regime-switching behavior across the sample period (2010–2024). Crucially, the reported 78% accuracy was obtained on the held-out test set data that was never exposed to the model during training confirming that this performance metric reflects the model's generalization capacity rather than memorization of training patterns. The validation loss, while exhibiting greater volatility than the training loss, did not display a sustained upward trend that would indicate severe overfitting, and the weighted F1-score of 0.78 across both crisis and non-crisis classes further supports the model's balanced predictive capability on unseen data.[2]

The overall performance of the model on the test set resulted in an accuracy of 78%, which is significant given the challenges inherent in predicting financial crises. As can be seen in Figure 4., the confusion matrix further illustrates the model's ability to distinguish between crisis and non-crisis periods, with 64 true negatives and 46 true positives. However, 13 false positives and 18 false negatives highlight areas where the model could be refined, particularly in distinguishing subtle market differences. As can be seen from Table 1., the precision, recall, and F1-score for both classes (crisis and non-crisis) were obtained in a relatively balanced manner, with a weighted F1-score of 0.78.

Figure 4. Confusion Matrix



Source: Author

[2] Training was conducted over 100 epochs with a batch size of 64, utilizing 80% of the dataset for training and reserving the remaining 20% for testing. The training process incorporated a validation split of 20% to monitor the model's performance on unseen data during training.

Table 1. presents the classification report regarding the performance of the LSTM model.

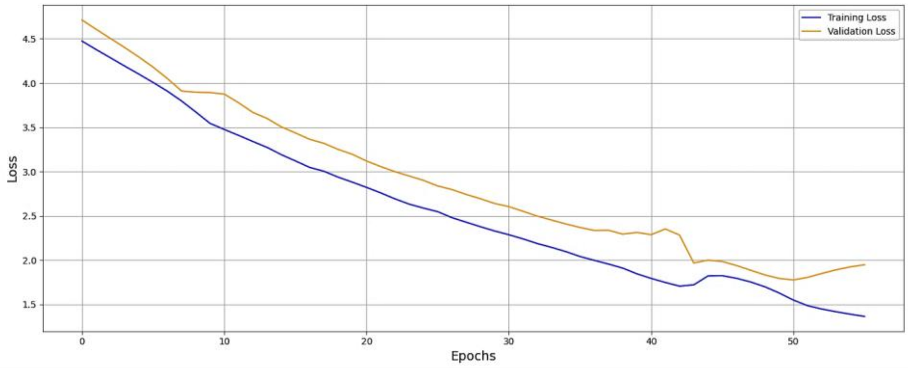
Table 1. Classification Report

	Precision	Recall	f1-Score	Support
0	0.78	0.83	0.81	77
1	0.78	0.72	0.75	64
Accuracy			0.78	141
Macro Avg	0.78	0.77	0.78	141
Weighted Avg	0.78	0.78	0.78	141

Source: Author

If Figure 5. is examined closely, it can be observed that both training and validation losses steadily decreased throughout the training process. However, the validation loss exhibited greater volatility, particularly around the 30th epoch, indicating that the model began to over-fit the training data at this point.

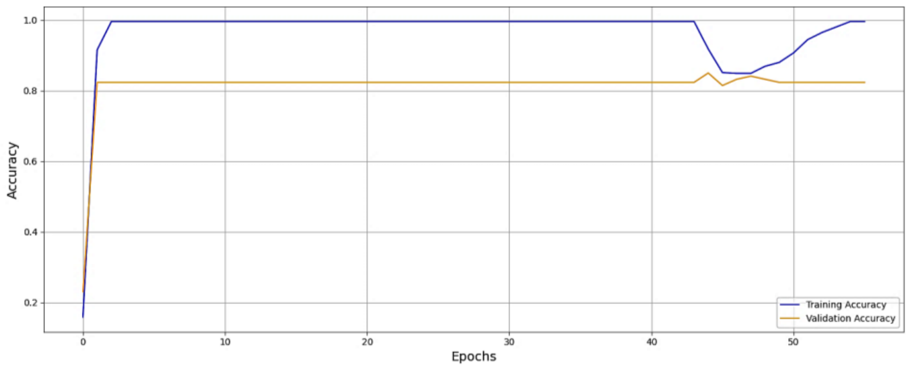
Figure 5. Trainining and Validation Loss for LSTM



Source: Author

Similarly, as shown in Figure 6., the training accuracy reached near-perfect levels early on, while the validation accuracy remained stable at around 82%. This suggests that the model generalizes well, but further tuning of hyperparameters such as dropout rates, regular-ization, or learning rate could enhance the model's performance on unseen data.

Figure 6. Trainining and Validation Accuracy for LSTM



Source: Author

The model’s ability to predict crisis probabilities based on forward steps could provide invaluable insights for policymakers and investors, enabling proactive measures in times of financial distress. The integration of CDS spreads and bond spreads is particularly effective in capturing the nuances of sovereign risk, and this framework could be expanded to include additional economic indicators to enhance predictive power.

The model's training and validation accuracy performance raises worries regarding possible overfitting problems during the relevant epoch values. This circumstance can be linked to the variable behavior shown by the CDS price series throughout time. To enhance the LSTM analysis throughout the modeling phase, or in simpler terms, to tackle or reduce the impacts of overfitting, possible strategies involve using 'class weights,' implementing 'early stopping,' and modifying the learning rate. The ultimate outcomes concerning model performance were attained through the application of these solutions.[3]

4.3. Future Crisis Probability Predictions

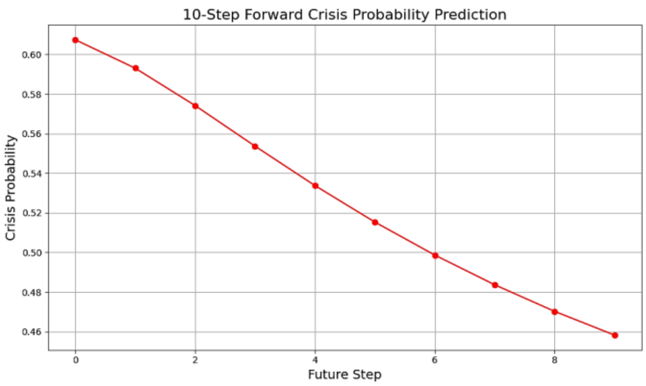
The results presented in Figure 7. illustrate the model's capacity to accurately forecast crisis probabilities across a defined time frame. The gradual decline observed in Figure 7. mirrors how potential hazards in financial markets develop over time. The crisis likelihood, which

[3] Although over-sampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique) and ADASYN (Adaptive Synthetic Sampling Approach for Imbalanced Learning) might theoretically be considered as solutions to mitigate the risk of overfitting, these methods were intentionally avoided. This decision was based on concerns that the mentioned techniques could introduce distortions into the sample set, potentially compromising the theoretical foundations while aiming to achieve the desired variability.

starts at a notable level in Step 1 (0.6074), significantly drops by Step 10 (0.4582), underscoring the model's responsiveness to shifts in market conditions. Such forecasts facilitate the early detection of financial crises, playing a pivotal role in the strategic decision-making process, especially in preparing for possible crises.

Proactive management of financial crises and market volatility is achievable not only through responses after a crisis but also through precautionary actions taken in the early phases of a crisis. Precisely predicting crisis probabilities empowers market actors and decision-makers to evaluate possible risks more efficiently. This allows for the crafting of more informed decisions, such as liquidity management, interest rate adjustments, and investment strategies, during periods of elevated risk. Furthermore, these modeling methods offer risk management experts valuable perspectives on the progression of risks over time, enabling stronger preparations against potential crises. In this regard, the early warning systems provided by the model will aid in establishing a more stable environment not just in financial markets but also in national and global economies.

Figure 7. Crisis Probabilities for the Next 10 Steps



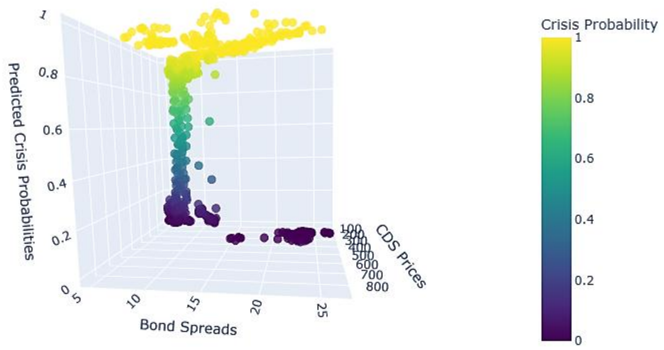
Source: Author

Figures 8. and 9. visualize the relationship between CDS spreads, bond spreads, and predicted crisis probabilities from a three-dimensional perspective. The horizontal axes represent CDS spreads and bond spreads, while the vertical axis shows the crisis probabilities predicted by the model. The color scale indicates the intensity of the predicted crisis probabilities, with lower probabilities represented by purple and higher probabilities by yellow. (Figure 9. presents a different angle of Figure 8. to enhance its interpretability).

The figures demonstrate that the risk of a crisis significantly increases as CDS spreads rise to higher levels and bond spreads widen. Specifically, in regions where CDS spreads exceed 600 and bond spreads surpass 20, the crisis probabilities predicted by the model rise sharply, reaching 80% or higher. This indicates that risk pricing in financial markets reflects both international credit risk and the disparity in borrowing costs among countries.

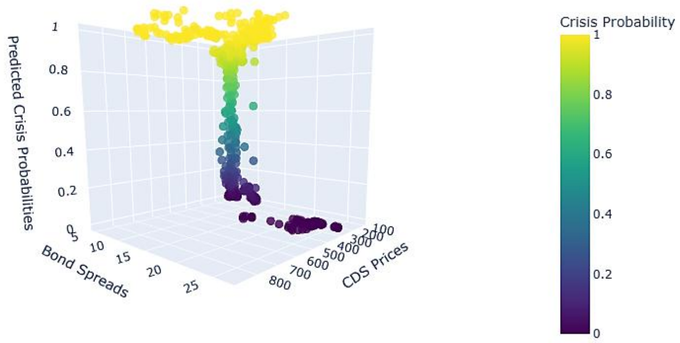
These findings confirm that the predicted crisis probabilities are strongly correlated with the CDS and bond spread indicators, which are commonly used to price macroeconomic risks. The model shows potential as a tool for early detection of crisis probabilities.

Figure 8. Crisis Prices, Bond Spreads and Predicted Crisis Probabilities



Source: Author

Figure 9. Crisis Prices, Bond Spreads and Predicted Crisis Probabilities (Alternative Viewpoint)



Source: Author

5. Discussion

The integration of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, with financial market indicators such as Credit Default Swaps (CDS) and sovereign bond spreads marks a significant advancement in the field of financial crisis prediction. This study not only underscores the capacity of LSTM networks to process complex temporal relationships inherent in financial data but also demonstrates the value of combining traditional market metrics with advanced machine learning models. The results illustrate that by capturing both the forward-looking nature of CDS spreads and the relative risk perceptions reflected in bond spreads, it is possible to develop a robust framework that provides early signals of financial distress.

One of the key contributions of this research lies in the application of the Logistic Smooth Transition Autoregressive (LSTAR) model to the CDS data. The LSTAR model's ability to identify critical thresholds within CDS pricing such as the 522.28 level discovered in this study sheds light on regime shifts in financial markets. These shifts are often precursors to financial instability, suggesting that the integration of nonlinear modeling techniques can significantly enhance the predictive power of conventional risk assessment frameworks. This threshold serves as a critical indicator for market practitioners and policymakers, providing a tangible benchmark around which to organize preemptive actions.

While the LSTM network exhibited a capacity to distinguish between crisis and non-crisis periods, it is important to acknowledge the model's limitations, particularly in its sensitivity to minor market fluctuations. The presence of false positives and false negatives indicates that while the model is effective in capturing broad market trends, it may struggle with subtle transitions that occur during the early stages of financial instability. Future research could explore more sophisticated architectures or hybrid models, such as combining LSTM with attention mechanisms or reinforcement learning, to improve the model's sensitivity and reduce forecasting errors.

Moreover, this study could expand the discussion regarding the increasing influence of machine learning in financial analysis. Although traditional econometric models have historically supported crisis predictions, they are often limited by assumptions of linearity and stationarity. The complex, non-linear characteristics of financial markets especially during periods of increased uncertainty require more flexible and reactive tools. The implementation of LSTM networks addresses some of these limitations; however, incorporating additional financial and macroeconomic factors could lead to a more comprehensive model that encompasses a broader range of risk factors. Including alternative data sources such as social media sentiment evaluations or geopolitical risk indicators could enhance the model's accuracy by considering external factors that influence market behavior.

From a policy perspective, the findings of this study are considered to be significant. Advanced crisis forecasting, which provides higher accuracy and earlier warnings, can offer regulators, central banks, and governments critical resources for managing systemic risk. In today's highly interconnected global financial environment, the rapid detection of weaknesses in one market can help prevent ripple effects in others. This research also aims to emphasize the importance of adaptable, data-driven risk management systems that combine traditional market indicators with advanced machine learning methods to proactively address emerging risks.

Nonetheless, it is equally important to take into account the ethical implications of using machine learning in finance. Although the enhanced predictive capabilities of these models present significant opportunities, excessive dependence on algorithmic forecasts should be approached with caution. Decision-makers and market participants must guarantee that human assessment is not completely replaced by automated analysis, since the unpredictability of market sentiment and infrequent, unexpected occurrences can still pose challenges for even the most sophisticated models. Achieving a balance between human skills and machine intelligence will be essential for effectively implementing these models in practical environments.

From a different perspective, this study can be seen as bridging the gap between traditional financial metrics and advanced machine learning techniques by integrating LSTM networks with CDS and bond spreads. However, these models require continuous refinement, particularly in enhancing market sensitivity, incorporating diverse data sources, and addressing the ethical considerations associated with their use. The potential of this approach to transform financial risk management is considered to be high. Nevertheless, it should not be overlooked that achieving the goal of safeguarding global financial stability will require ongoing collaboration among data scientists, financial experts, and policymakers.

5.1. Macroeconomic and Financial Consequences of the Projected Forward-Looking Crisis Probabilities

As illustrated in Figure 7., the initial likelihood of a financial downturn begins at roughly 60% and progressively decreases over time, settling at 46% by the tenth interval. This anticipated pattern carries several significant ramifications for capital markets and the broader economic landscape.

Uncertainty and Risk Valuation in Capital Markets

The crisis probability commencing at 60% in the early stages of Figure 7. suggests that prevailing market signals incorporate a substantial risk premium. This could result in an expansion of CDS differentials, an elevation in sovereign debt yield spreads, and a retreat from volatile assets. As participants in financial markets factor in unpredictability, they may gravitate toward safe-haven instruments, amplifying selling pressure on equities and high-yield securities.

Nevertheless, as the projection suggests a diminishing likelihood over time, eventually dropping below 50%, a gradual resurgence in market sentiment may materialize. This could contribute to reduced price fluctuations, a renewed inclination towards higher-risk investments, and the stabilization of long-term debt yields, accompanied by a recovery in stock markets. Such a development would assist Turkey in managing economic outlooks more effectively. A well-structured institutional framework capable of shaping expectations efficiently could, in turn, enhance the flexibility of policy measures in an economy that has endured structural fragilities due to persistent issues like inflation over the years.

Potential Outcomes for Monetary Authorities and Decision-Makers

In the short run, the elevated crisis likelihood of 60% may prompt the Central Bank of the Republic of Turkey to exercise heightened prudence in tightening monetary regulations. During phases of heightened unpredictability, the probability of increasing interest rates may diminish, and even liquidity-enhancing strategies could be taken into consideration.

However, as the anticipated crisis probabilities steadily decline, monetary authorities may interpret the downturn risk as less severe, enabling them to enforce contractionary policies with greater assurance. Specifically, in a scenario where inflationary pressures remain persistent, a reduction in crisis probability could facilitate the continuation of interest rate increases by the central bank.

Effects on the Real Economy

The steady decline in the likelihood of a financial downturn over time carries significant consequences for the productive sector. As the expected level of uncertainty diminishes, businesses may gain greater confidence in their capital allocation strategies. While firms might postpone investment outlays or scale back hiring in response to short-term unpredictability, an improvement in long-term expectations could foster a resurgence in corporate spending and credit expansion.

However, given that the estimated probabilities remain slightly below the 50% threshold, market instabilities cannot be considered entirely mitigated. This implies that both enterprises and households may persist with a prudent stance, maintaining caution in leveraging debt and engaging in high-risk financial activities.

Effects on International Financial Flows

During phases of heightened crisis probability within the Turkish economy particularly when macroeconomic indicators exhibit widespread and simultaneous deterioration capital flight, currency volatility, and amplified financial instability may arise. However, as these probabilities diminish over an extended horizon, this could lead to a reduction in risk premiums associated with the Turkish economy, a resurgence in capital inflows, and a replenishment of foreign currency reserves.

Furthermore, prominent asset managers and institutional investors from advanced economies may reallocate funds toward the Turkish market once they observe a decline in economic uncertainty.

This research offers a valuable perspective for assessing the potential dynamics of financial markets and the broader economy based on crisis probability projections. A high crisis likelihood in the initial phase highlights the necessity for monetary authorities to maintain a more vigilant stance, as well as the potential for abrupt financial movements, heightened market fluctuations, and increased uncertainty.

In the longer term, however, the reduction in these probabilities may signal stabilization in lending markets, strengthened investor confidence, and a potential recovery in economic activity. Nevertheless, the fact that probabilities do not entirely decline to zero suggests that certain risk elements persist, requiring financial policymakers to remain vigilant. Consequently, crisis projections should not rely on a singular methodology but rather be reinforced with multiple analytical approaches, continuously reassessed in accordance with prevailing market conditions.

6. Conclusion

This research has shown the efficacy of combining Long Short-Term Memory (LSTM) networks with essential financial metrics specifically Credit Default Swaps (CDS) and sovereign bond spreads in forecasting financial crises. The integration of these indicators offers a comprehensive perspective on sovereign risk, reflecting market sentiment through CDS spreads as well as relative risk perception through bond yield spreads. This combined strategy has shown to be especially useful in simulating the dynamic, nonlinear characteristics present in financial markets, particularly in times of economic hardship.

The effective application of the Logistic Smooth Transition Autoregressive (LSTAR) model in this structure further improves the forecasting ability. The LSTAR model acts as a valuable instrument for detecting regime shifts by pinpointing crucial thresholds in CDS pricing, typically preceding financial instability. In this research, a threshold value of 522.28 for CDS spreads was discovered to indicate notable shifts in market dynamics, coinciding with the emergence of financial crises. This threshold-based regime-switching method facilitates a more detailed comprehension of the changing risk landscape, offering early warning signs that may be crucial in risk management tactics.

The LSTM network, trained on past datasets, showed a robust ability to predict crisis probabilities, reaching high accuracy in differentiating between crisis and non-crisis durations. Nonetheless, the existence of false positives and false negatives highlights opportunities for improvement, especially in increasing the model's sensitivity to subtle changes in market dynamics. Although the model attained a validation accuracy of 78%, suggesting encouraging outcomes, future endeavors could aim at fine-tuning model parameters to mitigate possible overfitting and improve generalization.

Going forward, adopting this LSTM-based model has significant ramifications for policymakers and investors. The ability to predict crises within a future-oriented period alongside the adaptive traits of CDS and bond spreads offers a proactive means for foreseeing financial difficulties. This predictive ability is crucial for reducing the effects of crises via prompt actions and educated choices.

In conclusion, this research contributes to the growing field of financial crisis prediction by enhancing the application of deep learning methods in conjunction with conventional financial metrics. Incorporating CDS and bond spreads into an LSTM framework offers a strong, data-oriented strategy that outshines traditional econometric techniques. Future research could expand on this study by incorporating additional financial and macroeconomic variables such as exchange rate volatility, foreign reserve adequacy, current account dynamics, and real sector indicators thereby enhancing the model’s predictive accuracy and relevance in various market contexts. This groundbreaking method could serve as a key tool in the early detection of financial crises, ultimately supporting initiatives to maintain global financial stability.

Declaration of Interest Statement:

The author declares no conflict of interest related to this article.

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