

Sovereign Credit Risk Comovement and Predictability During the U.S. Subprime Crisis: Evidence from Deep Learning

Yi-Long Hsiao

Faculty of Department of Finance,
National Dong Hwa University
Hualien, 974301 Taiwan (R.O.C.)
Tel : +886-3-8903147
E-mail : hsiao@gms.ndhu.edu.tw

Chien-Jung Ting (Corresponding Author)

Faculty of Dept. of Leisure, Recreation, and Tourism Management,
Southern Taiwan University of Science and Technology
Tainan, 71005 Taiwan (R.O.C.)
Tel : +886-6-253-3131 ext.4923
E-mail : cjting@stust.edu.tw

Sovereign Credit Risk Comovement and Predictability During the U.S. Subprime Crisis: Evidence from Deep Learning

Abstract

This study investigates the cross-country comovement and predictive relationships between U.S. sovereign credit risk and global sovereign credit default swap (CDS) spreads during the 2008 U.S. subprime mortgage crisis. To capture the nonlinear and dynamic characteristics of sovereign risk transmission, this study employs deep learning models, including multilayer perceptron (MLP) and convolutional neural networks (CNN), to forecast sovereign CDS movements across 61 countries.

The empirical results indicate that most countries exhibit positive comovement with U.S. sovereign risk. Under the MLP model, 77.05% of the sample countries display positive correlations, while the proportion rises slightly to 78.69% under the CNN model, suggesting substantial global sovereign risk interconnectedness during the crisis period. Nevertheless, the magnitude of the correlations varies across countries, reflecting heterogeneity in financial openness and macroeconomic conditions.

Several peripheral Eurozone economies exhibit negative correlations, implying that their sovereign risk dynamics became increasingly influenced by domestic fiscal and financial conditions during the European sovereign debt crisis. Model comparisons further indicate that CNN generally outperforms MLP, underscoring the importance of nonlinear structures and localized temporal dynamics in sovereign risk modeling. Compared with conventional time-series approaches, deep learning models generally demonstrate stronger predictive performance in capturing complex cross-market linkages.

Overall, the findings suggest that global sovereign risk comovements during financial crises are characterized by nonlinearity, heterogeneity, and time-varying dynamics, while deep learning provides a tractable framework for modeling systemic sovereign risk interconnectedness.

Keywords: U.S. subprime mortgage crisis; sovereign CDS spreads; deep learning; multilayer perceptron (MLP); convolutional neural networks (CNN)

JEL codes: E50; E60; F33; F34

1. Motivation

This study examines the relationship between U.S. sovereign credit risk and sovereign credit default swap (CDS) spreads across countries during the 2008 U.S. subprime mortgage crisis. As the crisis unfolded, the U.S. government implemented a series of fiscal and monetary policy measures to stabilize financial markets and support economic recovery. Given the central role of the United States in the global financial system, changes in U.S. policy and market conditions were rapidly transmitted internationally through channels such as capital flows, cross-border financial exposure, and shifts in investor risk appetite. This study therefore focuses on major crisis-related events and policy announcements to investigate cross-country sovereign risk comovements.

In the literature, sovereign CDS spreads are widely regarded as a market-based proxy for sovereign credit risk. Evidence from the European Central Bank suggests that CDS spreads efficiently reflect market perceptions of default risk and respond rapidly to new information. Accordingly, this study employs sovereign CDS spreads to capture real-time sovereign risk pricing dynamics during the crisis period.

Regarding data and event identification, this study focuses on major events associated with the subprime crisis between 2008 and 2009. Drawing on Dooley and Hutchison (2009), together with official timelines from the Federal Reserve Bank of St. Louis and market records from Bloomberg L.P., this study identifies 15 representative policy and market events. Each event date serves as a reference point for evaluating the dynamic responses of global sovereign risk to crisis shocks and policy developments.

Compared with previous studies, which generally focus on emerging markets or a limited number of countries, this study extends the analysis to a global sample of 61 countries. This broader coverage allows a broader assessment of sovereign risk comovements across countries and highlights substantial heterogeneity in cross-country linkages.

Methodologically, this study employs deep learning models, including multilayer perceptron (MLP) and convolutional neural networks (CNN), to capture nonlinear and dynamic features in sovereign risk. Relative to conventional time-series approaches,

deep learning models are better suited to handling high-dimensional data and complex nonlinear structures, particularly in financial environments characterized by noise, asymmetry, and structural change. These models are therefore employed to capture nonlinear sovereign risk dynamics and to evaluate the extent to which deep learning improves predictive performance relative to conventional econometric approaches.

The empirical results indicate that sovereign CDS spreads in most countries are positively associated with U.S. sovereign risk, suggesting widespread cross-country comovement. Overall, deep learning models outperform traditional time-series approaches in capturing nonlinear and dynamic characteristics. This study makes three main contributions. First, it extends the analysis to a global sample, providing cross-country evidence on sovereign risk comovements. By covering 61 countries and systematically examining the dynamics of the 2008–2009 U.S. subprime mortgage crisis, this study offers a broader perspective on global financial interconnectedness. Second, this study applies deep learning techniques to effectively capture nonlinear and dynamic structures in sovereign risk. Third, this study provides new empirical evidence on systemic risk linkages during financial crises.

Accordingly, the term “cross-country comovement” in this study refers to the predictive and synchronous dynamic relationships between sovereign CDS spreads across countries and U.S. CDS movements, rather than a strict causal spillover effect in the conventional sense.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodology and model specifications. Section 4 describes the data and variables. Section 5 reports the empirical results. Section 6 concludes.

2. Literature Review

2.1 Cross-Country Sovereign Risk Comovements During Financial Crises

Sovereign credit default swap (CDS) spreads are widely regarded as a market-based measure of sovereign credit risk. Following the 2008 U.S. subprime mortgage crisis, the rapid propagation of financial distress across global markets intensified attention toward the cross-country transmission and comovement of sovereign risk. Prior studies suggest that sovereign CDS spreads reflect not only domestic macroeconomic

fundamentals, but also global risk sentiment, international capital flows, and common financial market factors (Pan and Singleton, 2008). Dieckmann and Plank (2012) further show that sovereign CDS spreads during the global financial crisis were closely associated with both domestic economic conditions and global financial sentiment.

Cross-country sovereign risk transmission became particularly pronounced during crisis periods. Fontana and Scheicher (2010) document substantial contagion and common volatility dynamics in European sovereign CDS markets during the financial crisis. Longstaff et al. (2011) further demonstrate that U.S. financial market risk can influence sovereign risk conditions in other countries through global financial integration and portfolio rebalancing channels. Similarly, Ang and Longstaff (2013) find that systemic sovereign credit risk exhibits strong common movement during crises, implying that global financial risk factors simultaneously affect sovereign risk across countries. More recent evidence suggests that sovereign CDS comovements are characterized by significant nonlinearities and asymmetries, particularly during periods of financial stress (Bampinas et al., 2023). In addition, geopolitical events and heightened uncertainty may further amplify systemic interconnectedness and risk contagion in global sovereign CDS markets (Shen et al., 2024).

2.2 Applications of Machine Learning and Deep Learning in Financial Risk Forecasting

In recent years, machine learning (ML) and deep learning approaches have been increasingly applied in finance, becoming increasingly important in risk assessment and asset pricing. Existing studies suggest that machine learning models possess important advantages in handling high-dimensional data and nonlinear relationships, thereby improving predictive accuracy and model performance (Lopez de Prado, 2018; Lin, 2020). Consequently, these approaches have been widely adopted in areas such as credit risk analysis, investment strategies, and financial forecasting.

2.2.1 Multilayer Perceptron (MLP) Models

Multilayer perceptron (MLP) is among the earliest deep learning models widely applied in financial forecasting. Owing to its strong nonlinear approximation capability, MLP has been extensively used in credit risk and default prediction (Delashmit et al., 2005; Ramchoun et al., 2016).

2.2.2 Convolutional Neural Network (CNN) Models

Although convolutional neural networks (CNNs) were originally developed for image recognition, they have increasingly been applied to financial time-series analysis. Prior studies indicate that CNN models effectively capture localized fluctuations and nonlinear features in financial data, particularly in markets characterized by structural breaks and substantial volatility (LeCun et al., 1998; Liao, 2019). Relative to conventional linear models, CNNs are generally more capable of identifying localized extreme movements, structural changes, and temporal asymmetries during financial crises, making them potentially more suitable for analyzing dynamic cross-country sovereign CDS comovements.

2.2.3 Other Machine Learning and Deep Learning Approaches

Beyond MLP and CNN models, a growing literature applies alternative machine learning methods to financial forecasting, asset pricing, and credit risk analysis, demonstrating superior predictive performance under high-dimensional and nonlinear settings (Gu et al., 2020; Uysal and Mulvey, 2021).

Related studies have also examined machine learning applications in credit risk and financial distress prediction. Odom and Sharda (1990), Tam and Kiang (1992), Huang et al. (2004), and Butaru et al. (2016) show that machine learning models generally outperform traditional statistical approaches in forecasting default risk and credit ratings. Similarly, Barboza et al. (2017) and Min and Jeong (2009) report strong predictive performance in forecasting bank failures and corporate financial distress.

2.3 Research Gap and Contributions

During financial crises, sovereign CDS spreads often exhibit substantial volatility, structural breaks, and nonlinear dynamics. Under such conditions, deep learning approaches may better capture the nonlinear and dynamic characteristics of cross-country sovereign risk comovements.

Although previous studies have extensively examined machine learning applications in credit risk analysis and financial forecasting, most focus primarily on firm-level default risk, asset pricing, or investment strategies. Relatively limited attention has been devoted to the cross-country comovement and predictive relationships of global sovereign credit risk. Moreover, the sovereign CDS literature has largely relied on conventional linear models to analyze risk transmission and cointegration relationships, while the applicability of deep learning methods to sovereign risk comovements during crisis periods remains underexplored.

Accordingly, this study employs MLP and CNN models to examine the cross-country comovement and predictive relationships of sovereign credit risk during the U.S. subprime mortgage crisis. In addition, this study compares the performance of deep learning and traditional time-series models in capturing the dynamic interconnectedness of sovereign risk across countries.

3. Methodology

To capture the nonlinear dynamics and high-dimensional interactions in credit default swap (CDS) spreads, this study adopts deep learning models as the primary analytical framework, complemented by traditional time-series models for comparison. In particular, multilayer perceptron (MLP) and convolutional neural networks (CNN) possess automatic feature-learning and nonlinear mapping capabilities, enabling them to capture both global structures and localized temporal patterns in financial data. By contrast, conventional approaches—including autoregressive distributed lag (ARDL), nonlinear ARDL (NARDL), fully modified ordinary least squares (FMOLS), and nonlinear FMOLS (NFMOLS)—provide strong theoretical interpretability and long-run equilibrium analysis, but remain relatively limited in handling substantial nonlinearities and structural breaks. This study therefore evaluates the relative advantages of deep learning models in forecasting sovereign credit risk.

(A) Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) is a feed-forward neural network that learns complex nonlinear relationships through multilayer transformations. Let the input matrix be $X \in \mathbb{R}^{n \times p}$. The MLP mapping function is specified as:

$$f(X) = W_3(\sigma(W_2\sigma(W_1X + b_1) + b_2)) + b_3 \quad (1)$$

where W_i and b_i denote the weight matrices and bias vectors, respectively, and $\sigma(\cdot)$ represents the activation function. The hidden layers employ the hyperbolic tangent (tanh) activation function, while the output layer adopts a linear activation function to accommodate continuous CDS spread prediction.

Model training is conducted using the Nadam optimizer (Dozat, 2016), which combines adaptive learning rates with Nesterov momentum to improve convergence

and optimization stability. The loss function is defined as the mean squared error (MSE):

$$\mathcal{L}_{MLP} = \frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2 \quad (2)$$

To improve generalization, optimal hyperparameters—including hidden units, learning rate, and batch size—are selected via grid search. Early stopping is further implemented to mitigate overfitting. Training terminates when validation loss fails to improve for p consecutive iterations:

$$\mathcal{L}_{MLP}^{(t+p)} \geq \mathcal{L}_{MLP}^{(t)} \quad (3)$$

Model performance is evaluated using correlation (Corr), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). Owing to its strong nonlinear approximation capability, the MLP model is well suited to capturing complex CDS market dynamics.

(B) Convolutional Neural Networks (CNN)

To further capture localized temporal structures in CDS spreads, we employ convolutional neural networks (CNN). Through local connectivity and weight-sharing mechanisms, CNNs automatically extract important sequential features and are particularly suitable for financial time series characterized by regime shifts and volatility clustering. The model architecture consists of convolutional layers, pooling layers, a global average pooling layer, and fully connected layers.

The convolution operation is defined as:

$$a_c^{(l+1)}(n) = f\left(\sum_m \Sigma_i a_m^{(l)}(n+i) * k_{c,m}^{(l)}(i) + b_c^{(l)}\right) \quad (4)$$

where $k_{c,m}^{(l)}$ denotes the convolutional kernel weight, $b_c^{(l)}$ is the bias term, and $f(\cdot)$ represents the activation function (ReLU in this study).

The max-pooling operation is specified as:

$$p_c^{(l+1)}(n) = \max_{0 \leq i < P_{pool}} a_c^{(l)}(stride * n + i) \quad (5)$$

The global average pooling layer is defined as:

$$g_c^{(l+1)} = \frac{1}{L} \sum_{n=1}^L p_c^{(l)}(n) \quad (6)$$

The final output layer is given by:

$$y^{(l+1)} = f(W^{(l+1)} * g^{(l)} + b^{(l+1)}) \quad (7)$$

The loss function is likewise specified as the mean squared error:

$$\mathcal{L}_{CNN} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (8)$$

Model implementation is conducted in Python using Keras with TensorFlow backend.

To compare predictive performance between CNN and MLP models, this study tests the following hypotheses:

$$\begin{aligned} H_0: \mu_{CNN} - \mu_{MLP} &= 0 \\ H_1: \mu_{CNN} - \mu_{MLP} &\neq 0 \end{aligned} \quad (9)$$

Paired t-tests are conducted to evaluate whether differences in prediction errors between the two models are statistically significant. If $CNN - MLP > 0$, the CNN model is considered to exhibit superior predictive performance.

(C) Traditional Time-Series Models

In addition to deep learning models, this study employs ARDL, NARDL, FMOLS, and NFMOLS models for comparative analysis. The ARDL framework captures both short-run dynamics and long-run equilibrium relationships and is applicable to variables with mixed integration orders, while NARDL further allows for asymmetric effects of positive and negative changes. FMOLS and NFMOLS are used to estimate cointegration relationships while correcting for endogeneity and serial correlation, with NFMOLS additionally accommodating nonlinear adjustments.

Overall, traditional models provide theoretically interpretable long-run equilibrium relationships, whereas deep learning approaches offer greater flexibility in capturing nonlinear and high-dimensional dynamic structures. Comparing these approaches provides additional evidence on sovereign CDS comovements and predictability.

4. Data Description

The event dates examined in this study correspond to fiscal and monetary policy announcements issued by the U.S. government during the 2008 U.S. subprime mortgage crisis. Event identification follows Dooley and Hutchison (2009), supplemented by official timelines from the Federal Reserve Bank of St. Louis and market records from Bloomberg L.P. Based on these sources, this study identifies 18 representative policy and market events that capture major information shocks affecting market expectations. The corresponding event dates are reported in Table 1.

The sovereign credit risk data are obtained from Datastream. The primary variable is the U.S. dollar-denominated 5-year sovereign credit default swap (CDS) spread for each country. To measure sovereign risk relative to a benchmark economy, this study further constructs relative CDS spreads by subtracting Germany's sovereign CDS spread from that of each sample country. The full sample period spans from July 21, 2008 to May 20, 2010, covering the crisis outbreak, policy interventions, and subsequent market adjustment phases. The list of sample countries is provided in Appendix Table A0. Although the sample period extends into 2010, the primary focus of this study remains on the U.S. subprime mortgage crisis and the associated policy intervention and market adjustment processes.

[Insert Table 1 here]

The 15 selected events primarily capture major policy measures implemented by the U.S. government during the financial crisis. Under the efficient market hypothesis, if sovereign CDS markets incorporate available information efficiently, market reactions to homogeneous policy announcements should be concentrated around the initial disclosure date. Accordingly, this study adopts the first announcement date of each event as the event date, consistent with the related literature.

The sample includes sovereign CDS spreads for 61 countries, allowing for an examination of cross-country sovereign risk responses following crisis-related policy announcements. Cross-country comparisons further enable an assessment of the international transmission and heterogeneity of financial crisis shocks.

Regarding the observation window, the date of the final event (November 20, 2009) is used as the benchmark, with the sample extended by an additional six months. Combined with pre- and post-event observations, the overall study period is therefore

defined as July 21, 2008 to May 20, 2010. This interval captures the crisis outbreak, policy responses, and subsequent market adjustments, thereby allowing an assessment of the dynamic effects of the U.S. subprime mortgage crisis on global sovereign credit risk.

To evaluate robustness, this study further estimates 3-year and 10-year sovereign CDS spreads. Because market liquidity and data availability differ across maturities, the numbers of sample countries for the 3-year and 10-year contracts are slightly smaller than that for the 5-year benchmark maturity. The 5-year CDS spread is adopted as the primary benchmark because it is the most liquid and widely traded maturity in sovereign CDS markets, while the 3-year and 10-year results are used to assess whether the main findings remain robust across shorter- and longer-term measures of sovereign credit risk.

5. Empirical Results

5.1 Main Results: 5-Year CDS Spreads

[Insert Table 2 here]

Table 2 summarizes the main prediction results for the 5-year CDS spreads under both the MLP and CNN models, where the input variables consist of five lagged U.S. sovereign CDS spreads. Under the MLP specification, 3 countries exhibit highly positive correlations, 24 exhibit moderately positive correlations, and 20 exhibit weakly positive correlations. Overall, 47 countries display positive correlations, accounting for 77.05% of the sample. These findings indicate substantial sovereign risk interconnectedness across countries following the 2008 U.S. subprime mortgage crisis.

From an economic perspective, this widespread positive comovement may be explained through three primary transmission channels. First, cross-border financial exposure through banking systems and international portfolio linkages transmitted U.S. asset revaluations to other economies. Second, the decline in global risk appetite during the crisis (“risk-off” behavior) triggered capital outflows from riskier markets, thereby increasing sovereign CDS spreads. Third, tighter U.S. dollar liquidity and deteriorating global financing conditions raised sovereign risk premia, particularly for economies dependent on external financing, strengthening their comovement with U.S. CDS dynamics.

At the country level, Finland, the United Kingdom, and Sweden exhibit the highest correlations under the MLP model, suggesting strong synchronization with U.S. sovereign risk. These economies are characterized by mature financial systems, high capital mobility, and deep integration into global financial markets, rendering them more sensitive to external shocks. Moderately correlated countries are distributed across regions, implying that although sovereign risk comovement is global in nature, its intensity remains conditioned by macroeconomic fundamentals, fiscal conditions, and external vulnerability. Weakly correlated countries exhibit more limited linkages, often reflecting lower financial openness or weaker dependence on international capital markets.

By contrast, several countries exhibit negative correlations, particularly peripheral Eurozone economies such as Greece, Ireland, Italy, Portugal, and Spain. This pattern is consistent with the European sovereign debt crisis, during which sovereign risk in these countries became increasingly driven by domestic fiscal imbalances and banking sector fragility rather than global factors. Negative correlations therefore do not imply the absence of cross-country linkages, but instead reflect a shift in sovereign risk dynamics from global to domestic drivers.

[Insert Table 3 here]

Table 2 summarizes the main prediction results for the 5-year CDS spreads under both the MLP and CNN models. Table 3 reports the mean difference tests between the CNN and MLP models. Under the CNN specification, 3 countries exhibit highly positive correlations, 24 exhibit moderately positive correlations, and 21 exhibit weakly positive correlations. In total, 48 countries display positive correlations, accounting for 78.69% of the sample, slightly exceeding the 77.05% obtained under the MLP model. This finding further supports the existence of pervasive global sovereign risk comovement and suggests that CNN models provide modestly stronger predictive performance. The results imply that predictive accuracy improves when models are able to capture localized temporal fluctuations and nonlinear structures in financial time series.

Finland, Sweden, and Guatemala exhibit highly positive correlations under the CNN model, suggesting that sovereign risk responses to U.S. shocks contain localized and nonlinear temporal dynamics. Moderately correlated countries remain broadly distributed across regions, reflecting systemic linkages driven by global capital market revaluation, tighter U.S. dollar funding conditions, and declining investor

confidence. Negative correlations continue to be concentrated among peripheral Eurozone economies, further supporting the interpretation that sovereign risk dynamics in these countries became increasingly dominated by domestic factors.

Taken together, the MLP and CNN results indicate that most countries exhibit positive predictive relationships with U.S. sovereign risk, although predictive performance differs across models for some countries. Accordingly, this study further conducts mean difference tests to compare the relative forecasting performance of CNN and MLP models.

[Insert Table 4 here]

Table 4 compares the predictive performance of CNN and MLP models. Among the 61 sample countries, CNN significantly outperforms MLP in 39 countries (63.93%), whereas MLP significantly outperforms CNN in 16 countries (26.23%); the remaining 6 countries exhibit no statistically significant difference. Overall, the average CNN–MLP difference is positive, indicating superior predictive performance of CNN models in most cases.

These findings suggest that sovereign risk dynamics during crisis periods involve substantial heterogeneity and short-run adjustment patterns that conventional linear frameworks may not fully capture. Consequently, CNN models, which are designed to capture localized features, outperform MLP models in most countries. By contrast, the relatively stronger performance of MLP in a smaller subset of countries may reflect smoother sovereign risk dynamics with fewer concentrated short-run shocks.

Beyond comparing the two deep learning models, this study further contrasts their performance with traditional time-series approaches to evaluate the relative advantages of deep learning methods in analyzing sovereign risk comovement.

[Insert Table 5 here]

Table 5 summarizes the comparative results between deep learning models and traditional time-series approaches, including ARDL, NARDL, FMOLS, and NFMOLS. Compared with traditional models, both CNN and MLP generate predictive correlations for all sample countries, whereas traditional approaches identify stable linear or nonlinear long-run relationships in only a subset of countries. These results suggest that sovereign risk comovements during crises involve nonlinear,

asymmetric, and short-run dynamics beyond conventional long-run equilibrium relationships.

Notably, nonlinear traditional models (NARDL and NFMOLS) identify more countries with stable long-run equilibrium or cointegration relationships than linear models (ARDL and FMOLS), indirectly supporting the existence of nonlinear structures in the data. Nevertheless, their overall performance remains inferior to that of deep learning models, indicating that deep learning approaches possess greater flexibility in handling high-dimensional financial data and complex crisis-period dynamics.

Overall, the results in Tables 2–5 indicate that global sovereign credit risk during the 2008 U.S. subprime mortgage crisis exhibited substantial and widespread cross-country comovement, with considerable heterogeneity in both intensity and direction. Positive correlations are concentrated primarily among financially integrated economies, whereas negative correlations reflect countries whose sovereign risk dynamics became increasingly dominated by domestic factors. In general, deep learning models outperform traditional approaches in capturing nonlinear and dynamic sovereign risk linkages, with CNN models outperforming MLP models in most cases. These findings suggest that sovereign risk dynamics during global financial crises are nonlinear, time-varying, and heterogeneous.

5.2 Robustness Checks: 3-Year and 10-Year CDS Spreads

To examine whether the main findings are sensitive to CDS contract maturity, this study further re-estimates the MLP, CNN, and traditional time-series models using 3-year and 10-year sovereign CDS spreads and compares the results with the 5-year benchmark specification. Because data availability and market liquidity differ across maturities, the numbers of sample countries for the 3-year and 10-year CDS contracts are 57 and 58, respectively, slightly smaller than the 61-country benchmark sample. The purpose of this section is therefore to evaluate whether the predictive relationships identified in the benchmark specification remain robust across different maturity horizons.

The 3-year CDS results indicate that U.S. CDS spreads continue to maintain substantial predictive relationships with sovereign CDS spreads in most countries. Under the MLP model, 41 countries display positive correlations, accounting for 71.93% of the sample, whereas the CNN model identifies 44 positively correlated

countries (77.19%). These findings are broadly consistent with the benchmark results and suggest that sovereign risk linkages during the crisis were also reflected in shorter-term CDS pricing.

The relative performance of CNN models remains particularly strong for the 3-year maturity. Among the 57 sample countries, CNN significantly outperforms MLP in 37 countries (64.91%), whereas MLP significantly outperforms CNN in 19 countries (33.33%). This result suggests that shorter-maturity sovereign CDS spreads may contain greater short-run market fluctuations and more abrupt adjustments in investor expectations, which CNN models appear better able to capture.

The 10-year CDS results provide somewhat different evidence. Under the MLP model, 40 countries exhibit positive correlations (68.97%), while the CNN model identifies 42 positively correlated countries (72.41%). Although positive relationships remain dominant, the overall correlation levels are slightly weaker than those observed for the 3-year and 5-year maturities. In addition, MLP outperforms CNN in a larger number of countries. Specifically, among the 58 sample countries, CNN significantly outperforms MLP in 22 countries (37.93%), whereas MLP significantly outperforms CNN in 33 countries (56.90%).

One possible interpretation is that longer-maturity CDS spreads are more closely associated with persistent macroeconomic conditions, debt sustainability, and long-run institutional credibility. As a result, longer-horizon sovereign risk dynamics may evolve more smoothly over time, reducing the relative advantage of CNN models designed to capture concentrated short-run movements.

Overall, the robustness results broadly support the benchmark findings across alternative maturities. Regardless of whether 3-year, 5-year, or 10-year CDS spreads are employed, U.S. CDS spreads maintain positive predictive relationships with sovereign CDS spreads in most countries. At the same time, the relative performance of CNN and MLP models varies across maturities, suggesting that sovereign risk dynamics differ across the term structure of CDS contracts. In particular, shorter-maturity CDS spreads appear more sensitive to abrupt market adjustments and short-run fluctuations, whereas longer-maturity CDS spreads are more closely linked to persistent macroeconomic expectations and long-run sovereign fundamentals.

6. Conclusion

This study employs deep learning models to examine the cross-country predictive relationships between U.S. sovereign credit risk and sovereign CDS spreads during the 2008–2009 U.S. subprime mortgage crisis. Using multilayer perceptron (MLP) and convolutional neural networks (CNN), this study predicts sovereign CDS spreads for 61 countries based on U.S. CDS dynamics. The empirical results indicate that most countries exhibit positive predictive relationships with U.S. sovereign risk, suggesting substantial international sovereign risk interconnectedness during the crisis period.

Considerable heterogeneity is nevertheless observed across countries. While some economies exhibit relatively strong synchronization with U.S. CDS movements, others display weaker or even negative relationships, implying that sovereign risk dynamics differed according to country-specific economic and financial conditions. In particular, several peripheral Eurozone economies exhibit negative correlations, consistent with the view that sovereign risk pricing in these countries became increasingly influenced by regional debt-related factors during the European sovereign debt crisis.

In terms of model performance, CNN generally outperforms MLP for the 3-year and 5-year CDS maturities, whereas MLP performs relatively better for the 10-year maturity. These results suggest that shorter-maturity sovereign CDS spreads may contain more concentrated short-run adjustments and abrupt market fluctuations, while longer-maturity CDS spreads are more closely associated with persistent macroeconomic expectations and long-run sovereign fundamentals.

Compared with conventional time-series approaches, deep learning models generally provide stronger predictive performance in capturing heterogeneous sovereign risk dynamics across countries. The findings therefore suggest that nonlinear machine learning approaches may offer useful complementary tools for analyzing sovereign risk interconnectedness during periods of financial stress.

Nevertheless, several limitations remain. First, this study primarily focuses on predictive relationships between U.S. CDS spreads and sovereign CDS spreads across countries without explicitly incorporating macroeconomic variables, capital flows, or policy factors. Future research may extend the analysis to multivariate frameworks to further investigate the underlying transmission mechanisms. Second, the analysis primarily captures predictive comovement rather than strict causal relationships.

Future studies may strengthen causal identification through structural models or alternative identification strategies.

Overall, the findings suggest that sovereign risk dynamics during major financial crises are heterogeneous and maturity-dependent. More broadly, the findings suggest that deep learning approaches may provide a useful complementary framework for analyzing sovereign risk interconnectedness in highly integrated global financial markets.

Table 1. Major Financial and Policy Events During the U.S. Subprime Mortgage Crisis

No.	Date	Event Category	Event Description
1	May 6, 2008	Announcements of write-downs of U.S. financial institutions' assets	Fannie Mae reported a first-quarter loss of USD 2.19 billion.
2	Sep 15, 2008	Lehman Brothers event	Lehman Brothers filed for bankruptcy.
3	Sep 25, 2008	Bankruptcy or forced merger of U.S. financial institutions	Washington Mutual was seized by the FDIC, and JPMorgan Chase acquired its deposit operations.
4	Sep 29, 2008	Political developments in the United States	The U.S. Congress rejected the financial rescue plan.
5	Oct 10, 2008	Recapitalization announcements of U.S. financial institutions	General Electric raised USD 15 billion, while Warren Buffett invested USD 5 billion in preferred shares and warrants.
6	Oct 13, 2008	Expansion of Federal Reserve swap lines to industrialized economies	The Federal Reserve allowed European central banks to provide unlimited U.S. dollar liquidity and removed swap line limits.
7	Oct 29, 2008	Expansion of Federal Reserve swap lines to emerging economies	The FOMC established U.S. dollar swap lines of up to USD 30 billion each with Brazil, Mexico, South Korea, and Singapore.
8	Nov 12, 2008	Troubled Asset Relief Program (TARP)	The U.S. Treasury announced that TARP funds would no longer be used to purchase mortgage-related assets.
9	Nov 20, 2008	Policy announcements directly affecting the U.S. housing market	Fannie Mae and Freddie Mac announced a temporary suspension of foreclosure sales and eviction procedures for occupied properties through January 2009.
10	Nov 25, 2008	Policy announcements expanding the Federal Reserve's balance sheet	The Federal Reserve announced purchases of agency debt and mortgage-backed securities (MBS).
11	Dec 3, 2008	U.S. financial regulatory reforms	The SEC introduced measures to enhance transparency and accountability among credit rating agencies.
12	Dec 5, 2008	Policy announcements affecting the U.S. Treasury's balance sheet	The U.S. Treasury purchased preferred shares in banks under the Capital Purchase Program (CPP) as part of TARP capital injections.
13	Dec 11, 2008	Negative news on U.S. economic growth	The NBER announced that the U.S. economy had entered a recession in December 2007.
14	Dec 11, 2008	Positive news on U.S. economic growth	The U.S. House of Representatives approved a USD 14 billion bailout package for the automobile industry.
15	Jan 9, 2009	Adverse developments in U.S. credit markets	U.S. consumer borrowing fell by a record USD 7.9 billion, reflecting a further deepening of credit market stress.

Table 1. (Continued)

No.	Date	Event Category	Event Description
16	Feb 17, 2009	U.S. fiscal stimulus policy	The Barack Obama administration signed the American Recovery and Reinvestment Act (ARRA), introducing an economic stimulus package of approximately USD 787 billion.
17	Mar 18, 2009	Federal Reserve quantitative easing policy (QE1)	The Federal Reserve expanded its asset purchase program, including purchases of USD 750 billion in mortgage-backed securities and USD 300 billion in U.S. Treasury securities.
18	May 7, 2009	U.S. bank stress tests	The Federal Reserve released the results of the Supervisory Capital Assessment Program (SCAP) to evaluate the capital adequacy and stability of major financial institutions.

Source: Compiled from Dooley and Hutchison (2009), official timelines from the Federal Reserve Bank of St. Louis, and market-based records from Bloomberg.

Table 2. Summary Results for 5-Year CDS Spreads

Model	Number of Sample Countries	Highly Positive Correlation	Moderately Positive Correlation	Weakly Positive Correlation	Negative Correlation	Percentage of Positive Correlations	Average Corr
MLP	61	3	24	20	13	77.05%	0.1763
CNN	61	3	24	21	13	78.69%	0.2011

Table 3. CNN–MLP Mean Difference Tests

Maturity	Number of Sample Countries	CNN Significantly Outperforms MLP	MLP Significantly Outperforms CNN	No Significant Difference
3Y	57	37	19	1
5Y	61	39	16	6
10Y	58	22	33	3

Table 4. Comparison with Traditional Models

Maturity	CNN	MLP	ARDL	NARDL	FMOLS	NFMOLS
3Y	57 (100.00%)	57 (100.00%)	3 (5.26%)	19 (33.33%)	4 (7.02%)	38 (66.67%)
5Y	61 (100.00%)	61 (100.00%)	12 (19.67%)	32 (52.46%)	39 (63.93%)	29 (47.54%)
10Y	58 (100.00%)	58 (100.00%)	18 (31.03%)	41 (70.69%)	26 (44.83%)	39 (67.24%)

Notes:

- (1) The reported values indicate the number of countries identified by each model as exhibiting substantial comovement with U.S. sovereign CDS spreads; values in parentheses denote the corresponding percentage of the total sample for each maturity.
- (2) For the CNN and MLP models, comovement is determined based on the correlation coefficient (Corr) between predicted and actual values. For the ARDL, NARDL, FMOLS, and NFMOLS models, comovement is identified based on evidence of long-run equilibrium or cointegration relationships.
- (3) The total numbers of sample countries for the 3-year, 5-year, and 10-year CDS maturities are 57, 61, and 58, respectively.
- (4) Cointegration relationships in the ARDL and NARDL models are determined using the bounds test. For the FMOLS and NFMOLS models, cointegration is assessed based on the combined evidence from the Hansen parameter instability test, Park's added variables test, Engle–Granger test, and Phillips–Ouliaris test.

Table 5. Robustness Summary across CDS Maturities

Maturity	Model	Number of Sample Countries	Number of Positively Correlated Countries	Percentage of Positive Correlations	Number of Countries where CNN Outperforms MLP	Number of Countries where MLP Outperforms CNN
3Y	MLP	57	41	71.93%	37	19
3Y	CNN	57	44	77.19%		
5Y	MLP	61	47	77.05%	39	16
5Y	CNN	61	48	78.69%		
10Y	MLP	58	40	68.97%	22	33
10Y	CNN	58	42	72.41%		

References

- Addo, P. M., Guegan, D., & Hassani, B. (2018). Credit risk analysis using machine and deep learning models. *Risks*, 6(2), 38.
- Ang, A., & Longstaff, F. A. (2013). Systemic sovereign credit risk: Lessons from the U.S. and Europe. *Journal of Monetary Economics*, 60(5), 493–510.
- Bampinas, G., Panagiotidis, T., & Politsidis, P. N. (2023). Sovereign bond and CDS market contagion: A story from the Eurozone crisis. *Journal of International Money and Finance*, 137, 102897.
- Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, 83, 405–417.
- Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A. W., & Siddique, A. (2016). Risk and risk management in the credit card industry. *Journal of Banking & Finance*, 72, 218–239.
- Delashmit, W. H., Missiles, L. M., & Manry, M. T. (2005). Recent developments in multilayer perceptron neural networks.
- Dieckmann, S., & Plank, T. (2012). Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance*, 16(4), 903–934.
- Dooley, M., & Hutchison, M. (2009). Transmission of the U.S. subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis. *Journal of International Money and Finance*, 28(8), 1331–1349.
- Dozat, T. (2016). Incorporating Nesterov momentum into Adam. *Proceedings of the International Conference on Learning Representations (ICLR) Workshop*.
- Fontana, A., & Scheicher, M. (2010). An analysis of euro area sovereign CDS and their relation with government bonds. *European Central Bank Working Paper Series*, No. 1271.
- Galindo, J., & Tamayo, P. (2000). Credit risk assessment using statistical and machine learning: Basic methodology and risk modeling applications. *Computational Economics*, 15(1–2), 107–143.
- Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *Review of Financial Studies*, 33(5), 2223–2273.
- Huang, Z., Chen, H., Hsu, C.-J., Chen, W.-H., & Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: A market comparative study. *Decision Support Systems*, 37(4), 543–558.
- Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, 34(11), 2767–2787.

- LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278–2324.
- Liao, S. L. (2019). Analysis of the predictive ability of time series using convolutional neural network. *Journal of Futures and Options*, 12(3), 139–190.
- Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, 3(2), 75–103.
- Lopez de Prado, M. (2018). *Advances in financial machine learning*. Hoboken, NJ: John Wiley & Sons.
- Min, J. H., & Jeong, C. (2009). A binary classification method for bankruptcy prediction. *Expert Systems with Applications*, 36(3), 5256–5263.
- Odom, M. D., & Sharda, R. (1990). A neural network model for bankruptcy prediction. In *Proceedings of the International Joint Conference on Neural Networks* (pp. 163–168).
- Pan, J., & Singleton, K. J. (2008). Default and recovery implicit in the term structure of sovereign CDS spreads. *Journal of Finance*, 63(5), 2345–2384.
- Ramchoun, H., Ghanou, Y., Ettaouil, M., & Idrissi, M. A. J. (2016). Multilayer perceptron: Architecture optimization and training. *International Journal of Interactive Multimedia and Artificial Intelligence*, 4(1), 26–30.
- Shen, Y., Feng, Q. & Sun, X. (2024). Stability and risk contagion in the global sovereign CDS market under Russia-Ukraine conflict. *The North American Journal of Economics and Finance*, 74.
- Tam, K. Y., & Kiang, M. Y. (1992). Managerial applications of neural networks: The case of bank failure predictions. *Management Science*, 38(7), 926–947.
- Uysal, A. S., & Mulvey, J. M. (2021). A machine learning approach in regime-switching risk parity portfolios. *Journal of Financial Data Science*, 3(2), 87–108.

Appendix

Because the complete country-level estimation results for each model are extensive, the detailed results are reported in the Appendix in order to maintain the focus of the main text on the principal economic implications and overall comparative findings. To preserve readability, the main text reports only summary statistics and key model comparison results, while country-level correlation coefficients, prediction error measures, model difference tests, and comparisons with traditional time-series models are presented in full in Appendices A–C.

Appendix Table A0 first reports the sample country information, followed by Appendices A–C, which present the detailed estimation results for the 5-year, 3-year, and 10-year CDS spreads, respectively.

Table A0. Sample Countries

Region	Number of Countries	Countries
Latin America and the Caribbean	13	Argentina, Bahamas, Venezuela, Brazil, Chile, Colombia, Dominican Republic, El Salvador, Guatemala, Jamaica, Mexico, Panama, Peru
East Asia and Pacific	9	China, Hong Kong, Indonesia, Japan, Malaysia, Philippines, South Korea, Thailand, Vietnam
Europe and Central Asia	15	Croatia, Czech Republic, Denmark, Hungary, Iceland, Kazakhstan, Latvia, Lithuania, Poland, Romania, Serbia, Sweden, Switzerland, Turkey, United Kingdom
Middle East and North Africa	9	Algeria, Bahrain, Iraq, Israel, Lebanon, Morocco, Qatar, Tunisia, United Arab Emirates
South Asia	2	Pakistan, Sri Lanka
Eurozone Peripheral Countries	6	Cyprus, Greece, Ireland, Italy, Portugal, Spain
Eurozone Core Countries	7	Austria, Finland, France, Netherlands, Malta, Slovakia, Slovenia
Total	61	

Notes:

Regional classifications are based on broad geographical and financial market characteristics commonly adopted in the international finance literature.

General Notes for Appendix Tables

- (1) Corr denotes the correlation coefficient between predicted and actual sovereign CDS spreads. The reported correlation coefficients represent the average predictive correlations obtained from repeated out-of-sample forecasting experiments, rather than correlation inferences derived from conventional statistical significance tests.
- (2) All reported statistics are based on the average results obtained from 30 repeated out-of-sample forecasting experiments for each country.

(3) The correlation classifications are defined as follows: highly positive correlation ($\text{Corr} \geq 0.7$), moderately positive correlation ($0.3 \leq \text{Corr} < 0.7$), weakly positive correlation ($0 < \text{Corr} < 0.3$), weakly negative correlation ($-0.3 < \text{Corr} < 0$), moderately negative correlation ($-0.7 < \text{Corr} \leq -0.3$), and highly negative correlation ($\text{Corr} \leq -0.7$).

(4) Unless otherwise specified, country-level correlation classifications are based on the correlation coefficients obtained from the CNN model.

Appendix A. 5Y CDS Results

Table A1. Country-level Sovereign CDS Comovement Classification

Panel A. Highly Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Finland	0.803	0.836	Highly Positive
Sweden	0.772	0.786	Highly Positive
Guatemala	0.740	0.691	Moderately Positive
Subtotal 3 countries (4.92%)	Average 0.772	Average 0.771	

Panel B. Moderately Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
United Kingdom	0.688	0.809	Highly Positive
Bahamas	0.614	0.653	Moderately Positive
Qatar	0.562	0.566	Moderately Positive
Iraq	0.557	0.487	Moderately Positive
Bahrain	0.507	0.484	Moderately Positive
United Arab Emirates	0.499	0.523	Moderately Positive
Algeria	0.495	0.645	Moderately Positive
Austria	0.493	0.444	Moderately Positive
Hong Kong	0.487	0.562	Moderately Positive
Panama	0.478	0.444	Moderately Positive
Denmark	0.477	0.498	Moderately Positive
Iceland	0.474	0.412	Moderately Positive
Pakistan	0.457	0.432	Moderately Positive
China	0.443	0.445	Moderately Positive
Dominican Republic	0.437	0.375	Moderately Positive
Israel	0.431	0.436	Moderately Positive
Latvia	0.385	0.333	Moderately Positive
Serbia	0.384	0.345	Moderately Positive
Peru	0.348	0.316	Moderately Positive
Brazil	0.345	0.312	Moderately Positive
Slovakia	0.343	0.357	Moderately Positive
Sri Lanka	0.329	0.317	Moderately Positive
Slovenia	0.308	0.319	Moderately Positive
Vietnam	0.303	0.166	Weakly Positive
Subtotal 24 countries (39.34%)	Average 0.452	Average 0.447	

Panel C. Weakly Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Netherlands	0.300	0.339	Moderately Positive
Czech Republic	0.299	0.277	Weakly Positive
Jamaica	0.296	0.259	Weakly Positive
Philippines	0.292	0.232	Weakly Positive
Switzerland	0.269	0.029	Weakly Positive
Morocco	0.265	0.276	Weakly Positive
El Salvador	0.224	0.218	Weakly Positive
Mexico	0.203	0.172	Weakly Positive
Turkey	0.202	0.120	Weakly Positive

Lithuania	0.202	0.146	Weakly Positive
Tunisia	0.196	0.224	Weakly Positive
Indonesia	0.190	0.118	Weakly Positive
Argentina	0.187	0.148	Weakly Positive
Colombia	0.176	0.137	Weakly Positive
Malaysia	0.175	0.163	Weakly Positive
Kazakhstan	0.088	0.021	Weakly Positive
South Korea	0.075	0.063	Weakly Positive
Chile	0.073	0.075	Weakly Positive
Japan	0.056	0.086	Weakly Positive
Poland	0.044	0.013	Weakly Positive
Hungary	0.001	−0.051	Weakly Negative
Subtotal 21 countries (34.43%)	Average 0.182	Average 0.147	
Panel D. Weakly Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Croatia	−0.008	−0.059	Weakly Negative
Romania	−0.011	−0.064	Weakly Negative
Cyprus	−0.075	−0.142	Weakly Negative
Malta	−0.133	−0.149	Weakly Negative
Venezuela	−0.195	−0.171	Weakly Negative
Thailand	−0.285	−0.266	Weakly Negative
Subtotal 6 countries (9.84%)	Average −0.118	Average −0.129	
Panel E. Moderately Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Ireland	−0.398	−0.610	Moderately Negative
Italy	−0.436	−0.531	Moderately Negative
France	−0.555	−0.560	Moderately Negative
Spain	−0.555	−0.609	Moderately Negative
Greece	−0.663	−0.753	Highly Negative
Portugal	−0.675	−0.699	Moderately Negative
Subtotal 6 countries (9.84%)	Average −0.547	Average −0.616	
Panel F. Highly Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Lebanon	−0.721	−0.689	Moderately Negative
Subtotal 1 country (1.64%)	Average −0.721	Average −0.689	
Overall Summary			
Total Sample	Average Corr (CNN)	Average Corr (MLP)	
61 countries (100%)	Average 0.201	Average 0.176	

Table A1a. Forecast Performance across Correlation Categories

Correlation Category	Model	Average MAE	Average MSE	Average RMSE
Highly Positive	CNN	44.898	4,210.840	47.172
	MLP	21.674	644.211	22.924
Moderately Positive	CNN	180.571	269,598.470	183.108
	MLP	147.021	243,892.611	152.703
Weakly Positive	CNN	99.234	56,532.103	102.507
	MLP	80.606	42,556.867	84.971
Weakly Negative	CNN	180.096	116,810.245	185.273
	MLP	149.885	90,465.699	159.004
Moderately Negative	CNN	96.833	26,869.875	113.359
	MLP	109.928	36,438.447	136.238
Highly Negative	CNN	112.726	13,065.050	114.299
	MLP	27.333	1,176.113	34.291

Notes:

- (1) MAE, MSE, and RMSE denote mean absolute error, mean squared error, and root mean squared error, respectively.
- (2) All reported statistics represent cross-country average forecasting performance measures within each correlation category.

Table A2. Mean Difference Tests between CNN and MLP Models

Panel A. Countries where CNN Significantly Outperforms MLP

Country	Corr (CNN)	Corr (MLP)	CNN-MLP	t-value	Significance
Argentina	0.187	0.148	0.039	25.344	***
Austria	0.493	0.444	0.049	2.206	**
Bahrain	0.507	0.484	0.023	3.580	***
Brazil	0.345	0.312	0.033	13.409	***
Colombia	0.176	0.137	0.039	19.209	***
Croatia	-0.008	-0.059	0.051	31.905	***
Cyprus	-0.075	-0.142	0.067	5.600	***
Czech Republic	0.299	0.277	0.022	3.373	***
Dominican Republic	0.437	0.375	0.062	12.321	***
El Salvador	0.224	0.218	0.006	2.934	***
France	-0.555	-0.560	0.005	4.370	***
Greece	-0.663	-0.753	0.090	6.926	***
Guatemala	0.740	0.691	0.049	13.051	***
Hungary	0.001	-0.0508	0.052	22.231	***
Iceland	0.474	0.412	0.062	12.823	***
Indonesia	0.190	0.118	0.071	25.134	***
Iraq	0.557	0.487	0.070	11.160	***
Ireland	-0.398	-0.610	0.211	33.306	***
Italy	-0.436	-0.531	0.095	19.425	***
Jamaica	0.296	0.259	0.038	9.966	***
Kazakhstan	0.088	0.021	0.067	22.062	***
Latvia	0.385	0.333	0.053	13.689	***
Lithuania	0.202	0.146	0.056	25.520	***
Malaysia	0.175	0.163	0.012	5.991	***
Mexico	0.203	0.172	0.032	15.198	***
Pakistan	0.457	0.432	0.025	4.236	***
Panama	0.478	0.444	0.034	9.209	***
Peru	0.348	0.316	0.033	14.952	***
Philippines	0.292	0.232	0.061	21.851	***
Poland	0.044	0.013	0.032	5.859	***
Portugal	-0.675	-0.699	0.024	4.168	***
Romania	-0.011	-0.064	0.052	19.680	***
Serbia	0.384	0.345	0.040	8.462	***
South Korea	0.075	0.063	0.012	14.313	***
Spain	-0.555	-0.609	0.054	18.824	***
Sri Lanka	0.329	0.317	0.013	2.674	**
Switzerland	0.269	0.029	0.240	2.066	**
Turkey	0.202	0.120	0.082	24.424	***
Vietnam	0.303	0.166	0.137	29.483	***
Subtotal	Average		Average	Average	
39 countries (63.93%)	0.196	Average 0.140	0.056	14.350	

Panel B. Countries where MLP Significantly Outperforms CNN

Country	Corr (CNN)	Corr (MLP)	CNN-MLP	t-value	Significance
Algeria	0.495	0.645	-0.150	-20.333	***
Bahamas	0.614	0.653	-0.039	-8.877	***
Venezuela	-0.195	-0.171	-0.024	-6.760	***
Denmark	0.477	0.498	-0.021	-16.531	***
Finland	0.803	0.836	-0.033	-7.170	***
Hong Kong	0.487	0.562	-0.075	-14.265	***
Japan	0.056	0.086	-0.030	-5.468	***
Lebanon	-0.721	-0.689	-0.032	-5.503	***
Morocco	0.265	0.276	-0.011	-2.242	**
Netherlands	0.300	0.339	-0.039	-16.780	***
Slovenia	0.308	0.319	-0.011	-5.211	***
Sweden	0.772	0.786	-0.015	-3.009	***
Thailand	-0.285	-0.266	-0.020	-2.762	***
Tunisia	0.196	0.224	-0.027	-7.826	***
United Arab Emirates	0.499	0.523	-0.025	-3.778	***
United Kingdom	0.688	0.809	-0.121	-10.365	***
Subtotal	Average		Average	Average	
16 countries (26.23%)	0.284	Average 0.326	-0.042	-8.697	

Panel C. Countries with No Significant Difference

Country	Corr (CNN)	Corr (MLP)	CNN-MLP	t-value	Significance
Chile	0.073	0.075	-0.002	-1.177	N.S.
China	0.443	0.445	-0.001	-0.426	N.S.

Israel	0.431	0.436	−0.005	−1.443	N.S.
Malta	−0.133	−0.149	0.016	1.032	N.S.
Qatar	0.562	0.566	−0.004	−0.886	N.S.
Slovakia	0.343	0.357	−0.014	−0.831	N.S.
Subtotal	Average		Average	Average	
6 countries (9.84%)	0.287	Average 0.289	−0.002	−0.622	

Total Summary

Sample Countries	Average Corr (CNN)	Average Corr (MLP)	Average CNN–MLP
61 countries (100.00%)	0.201	0.176	0.025

Notes:

- (1) Corr(CNN) and Corr(MLP) denote the average correlation coefficients obtained from 30 repeated experiments for each country under the CNN and MLP models, respectively; CNN–MLP represents the difference between the average correlation coefficients of the two models.
- (2) To compare the predictive performance of the CNN and MLP models, this study conducts mean difference tests based on the correlation coefficients obtained from 30 repeated experiments for each country. The null hypothesis states that no significant difference exists between the mean correlation coefficients of the two models ($H_0: \mu_{CNN} - \mu_{MLP} = 0$), whereas the alternative hypothesis states that a significant difference exists ($H_1: \mu_{CNN} - \mu_{MLP} \neq 0$).
- (3) If the test result is statistically significant and $CNN - MLP > 0$, the CNN model is considered to significantly outperform the MLP model. Conversely, if the test result is statistically significant and $CNN - MLP < 0$, the MLP model is considered to significantly outperform the CNN model. If the test result is not statistically significant, no significant difference is identified between the two models.
- (4) Statistical significance is defined as follows: *** $p < 0.01$; ** $p < 0.05$. N.S. denotes no statistically significant difference between the CNN and MLP models.

Table A3. Cross-model Identification of Sovereign Risk Linkages

Panel A. Cross-model Identification Results by Predictive Correlation Category

Correlation Category	Sample Countries	CNN	MLP	ARDL	NARDL	FMOLS	NFMOLS
Highly Positive	3	3 (100%)	3 (100%)	0 (0%)	2 (66.7%)	3 (100%)	3 (100%)
Moderately Positive	24	24 (100%)	24 (100%)	7 (29.2%)	12 (50.0%)	16 (66.7%)	14 (58.3%)
Weakly Positive	21	21 (100%)	21 (100%)	5 (23.8%)	13 (61.9%)	15 (71.4%)	9 (42.9%)
Weakly Negative	6	6 (100%)	6 (100%)	0 (0%)	3 (50.0%)	4 (66.7%)	3 (50.0%)
Moderately Negative	6	6 (100%)	6 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Highly Negative	1	1 (100%)	1 (100%)	0 (0%)	1 (100%)	0 (0%)	1 (100%)

Panel B. Overall Identification Results

Model	Countries Identified	Percentage
CNN	61	100.00%
MLP	61	100.00%
ARDL	12	19.67%
NARDL	32	52.46%
FMOLS	39	63.93%
NFMOLS	29	47.54%

Notes:

- (1) Cointegration relationships in the ARDL and NARDL models are determined using the bounds test. For the FMOLS and NFMOLS models, cointegration is assessed based on the combined evidence from the Hansen parameter instability test, Park’s added variables test, and the Engle–Granger and Phillips–Ouliaris cointegration tests.
- (2) “Model Identification” refers to the proportion of countries within each correlation category that are identified by a given model as exhibiting substantial comovement with U.S. CDS spreads. For example, 3/4 indicates that, among the four countries within a given category, three are identified by the model as exhibiting significant linkage characteristics.
- (3) “Overall Summary” reports the total number and proportion of countries, among all 61 sample countries, identified by each model as exhibiting comovement with U.S. CDS spreads. This summary facilitates comparisons between deep learning models and traditional time-series approaches in identifying cross-country sovereign credit risk linkages.

Appendix B. 3Y CDS Results

Table B1. Country-level Correlation Classification under CNN and MLP Models**Panel A. Highly Positive Correlation under CNN**

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Sweden	0.817	0.811	Highly Positive
Guatemala	0.770	0.768	Highly Positive
Finland	0.741	0.846	Highly Positive
United Kingdom	0.706	0.696	Moderately Positive
Subtotal 4 countries (7.02%)	Average 0.759	Average 0.780	

Panel B. Moderately Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
United Arab Emirates	0.654	0.664	Moderately Positive
Serbia	0.648	0.637	Moderately Positive
Iraq	0.647	0.638	Moderately Positive
Pakistan	0.644	0.629	Moderately Positive
Qatar	0.634	0.652	Moderately Positive
Dominican Republic	0.633	0.573	Moderately Positive
Iceland	0.615	0.583	Moderately Positive
Hong Kong	0.599	0.634	Moderately Positive
Denmark	0.578	0.599	Moderately Positive
Morocco	0.575	0.537	Moderately Positive
Bahamas	0.568	0.676	Moderately Positive
Bahrain	0.560	0.603	Moderately Positive
Panama	0.554	0.537	Moderately Positive
China	0.536	0.544	Moderately Positive
Latvia	0.516	0.476	Moderately Positive
Jamaica	0.514	0.413	Moderately Positive
Israel	0.479	0.457	Moderately Positive
Austria	0.452	0.403	Moderately Positive
Slovakia	0.416	0.379	Moderately Positive
Czech Republic	0.405	0.373	Moderately Positive
Slovenia	0.400	0.386	Moderately Positive
Philippines	0.394	0.362	Moderately Positive
Brazil	0.377	0.359	Moderately Positive
Indonesia	0.376	0.311	Moderately Positive
Peru	0.375	0.352	Moderately Positive
Chile	0.356	0.382	Moderately Positive
El Salvador	0.344	0.267	Weakly Positive
Tunisia	0.312	0.321	Moderately Positive
Lithuania	0.311	0.249	Weakly Positive
Mexico	0.310	0.251	Weakly Positive
Subtotal 30 countries (52.63%)	Average 0.506	Average 0.475	

Panel C. Weakly Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Netherlands	0.259	0.294	Weakly Positive
Malaysia	0.196	0.201	Weakly Positive
Kazakhstan	0.176	0.123	Weakly Positive
Colombia	0.175	0.175	Weakly Positive
Argentina	0.170	0.197	Weakly Positive
South Korea	0.162	0.158	Weakly Positive
Poland	0.061	0.016	Weakly Positive
Turkey	0.049	-0.121	Weakly Negative
Hungary	0.031	-0.025	Weakly Negative
Croatia	0.023	-0.021	Weakly Negative
Subtotal 10 countries (17.54%)	Average 0.130	Average 0.100	

Panel D. Weakly Negative Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Romania	-0.011	-0.043	Weakly Negative
Cyprus	-0.208	-0.182	Weakly Negative
Malta	-0.216	-0.194	Weakly Negative
Subtotal 3 countries (5.26%)	Average -0.145	Average -0.140	

Panel E. Moderately Negative Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Venezuela	-0.317	-0.268	Weakly Negative

France	−0.493	−0.497	Moderately Negative
Thailand	−0.522	−0.492	Moderately Negative
Ireland	−0.579	−0.602	Moderately Negative
Italy	−0.610	−0.642	Moderately Negative
Spain	−0.641	−0.672	Moderately Negative
Algeria	−0.700	−0.692	Moderately Negative
Subtotal 7 countries (12.28%)	Average −0.552	Average −0.552	
Panel F. Highly Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Portugal	−0.703	−0.734	Highly Negative
Greece	−0.728	−0.722	Highly Negative
Lebanon	−0.894	−0.899	Highly Negative
Subtotal 3 countries (5.26%)	Average −0.775	Average −0.785	
Overall Summary			
Sample Countries	Average Corr (CNN)	Average Corr (MLP)	
57 countries (100.00%)	0.219	0.206	

Table B1a. Forecast Performance Summary across Correlation Categories

Correlation Category	Model	Average MAE	Average MSE	Average RMSE
Highly Positive	CNN	34.774	2,997.903	37.477
	MLP	17.591	502.324	19.196
Moderately Positive	CNN	179.744	251,291.691	192.084
	MLP	135.805	176,637.488	142.275
Weakly Positive	CNN	107.392	73,735.741	111.116
	MLP	94.993	57,354.639	98.940
Weakly Negative	CNN	42.828	2,873.708	44.593
	MLP	21.884	568.669	23.749
Moderately Negative	CNN	154.528	104,246.224	159.703
	MLP	132.741	80,908.759	137.319
Highly Negative	CNN	194.703	71,411.636	224.580
	MLP	162.426	63,818.023	195.205

Notes:

- (1) MAE, MSE, and RMSE denote mean absolute error, mean squared error, and root mean squared error, respectively.
- (2) All reported statistics represent cross-country average forecasting performance measures within each correlation category.

Table B2. Comparison of Cross-country Linkage Identification across Models

Panel A. Cross-model Identification Results by Predictive Correlation Category

Correlation Category	Sample Countries	CNN	MLP	ARDL	NARDL	FMOLS	NFMOLS
Highly Positive	4	4 (100%)	4 (100%)	0 (0%)	3 (75.0%)	0 (0%)	3 (75.0%)
Moderately Positive	30	30 (100%)	30 (100%)	3 (10.0%)	12 (40.0%)	2 (6.7%)	18 (60.0%)
Weakly Positive	10	10 (100%)	10 (100%)	0 (0%)	3 (30.0%)	1 (10.0%)	7 (70.0%)
Weakly Negative	3	3 (100%)	3 (100%)	0 (0%)	0 (0%)	1 (33.3%)	3 (100%)
Moderately Negative	7	7 (100%)	7 (100%)	0 (0%)	1 (14.3%)	0 (0%)	2 (28.6%)
Highly Negative	3	3 (100%)	3 (100%)	0 (0%)	1 (33.3%)	0 (0%)	1 (33.3%)

Panel B. Overall Identification Results

Model	Countries Identified	Percentage
CNN	57	100.00%
MLP	57	100.00%

ARDL	3	5.26%
NARDL	19	33.33%
FMOLS	4	7.02%
NFMOLS	38	66.67%

Notes:

(1) Cointegration relationships in the ARDL and NARDL models are determined using the bounds test. For the FMOLS and NFMOLS models, cointegration is assessed based on the combined evidence from the Hansen parameter instability test, Park's added variables test, and the Engle–Granger and Phillips–Ouliaris cointegration tests.

(2) “Model Coverage” refers to the proportion of countries within each correlation category identified by a given model as exhibiting significant comovement with U.S. CDS spreads. For example, 3/4 indicates that, among the four countries within a given category, three are identified by the model as exhibiting significant linkage characteristics.

(3) “Overall Summary” reports the total number and proportion of countries, among all 57 sample countries, identified by each model as exhibiting comovement with U.S. CDS spreads. This summary facilitates comparisons between deep learning models and traditional time-series approaches in identifying cross-country sovereign credit risk linkages.

Appendix C. 10Y CDS Results

Table C1. Country-level Correlation Classification under CNN and MLP Models

Panel A. Highly Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Sweden	0.803	0.777	Highly Positive
Guatemala	0.735	0.692	Moderately Positive
Subtotal 2 countries (3.45%)	Average 0.769	Average 0.734	

Panel B. Moderately Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
United Kingdom	0.653	0.879	Highly Positive
Finland	0.628	0.868	Highly Positive
Israel	0.608	0.710	Highly Positive
Qatar	0.587	0.691	Moderately Positive
Denmark	0.567	0.583	Moderately Positive
Panama	0.528	0.602	Moderately Positive
United Arab Emirates	0.524	0.673	Moderately Positive
Bahrain	0.520	0.672	Moderately Positive
Serbia	0.500	0.664	Moderately Positive
Pakistan	0.494	0.660	Moderately Positive
Iraq	0.493	0.662	Moderately Positive
Hong Kong	0.474	0.612	Moderately Positive
Iceland	0.459	0.575	Moderately Positive
Netherlands	0.458	0.480	Moderately Positive
Dominican Republic	0.455	0.558	Moderately Positive
Morocco	0.433	0.560	Moderately Positive
China	0.409	0.471	Moderately Positive
Latvia	0.378	0.450	Moderately Positive
Austria	0.374	0.409	Moderately Positive
Bahamas	0.369	0.639	Moderately Positive
Philippines	0.344	0.370	Moderately Positive
Brazil	0.336	0.336	Moderately Positive
Jamaica	0.311	0.393	Moderately Positive
Subtotal 23 countries (39.66%)	Average 0.494	Average 0.594	

Panel C. Weakly Positive Correlation under CNN

Country	Corr (CNN)	Corr (MLP)	MLP Classification
Peru	0.299	0.297	Weakly Positive
Czech Republic	0.286	0.319	Moderately Positive
Slovenia	0.282	0.324	Moderately Positive
Indonesia	0.279	0.302	Moderately Positive
Slovakia	0.240	0.279	Weakly Positive
Malaysia	0.204	0.261	Weakly Positive
Argentina	0.191	0.217	Weakly Positive
El Salvador	0.172	0.197	Weakly Positive
Lithuania	0.162	0.147	Weakly Positive

Mexico	0.150	0.136	Weakly Positive
Turkey	0.115	0.005	Weakly Positive
Colombia	0.085	0.034	Weakly Positive
Kazakhstan	0.050	−0.018	Weakly Negative
Poland	0.038	0.006	Weakly Positive
South Korea	0.035	0.036	Weakly Positive
Chile	0.032	−0.018	Weakly Negative
Tunisia	0.004	0.038	Weakly Positive
Subtotal 17 countries (29.31%)	Average 0.151	Average 0.145	
Panel D. Weakly Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Romania	−0.006	−0.049	Weakly Negative
Croatia	−0.006	−0.054	Weakly Negative
Hungary	−0.013	−0.055	Weakly Negative
Japan	−0.058	−0.052	Weakly Negative
Cyprus	−0.176	−0.167	Weakly Negative
Malta	−0.194	−0.177	Weakly Negative
Venezuela	−0.227	−0.279	Weakly Negative
Ireland	−0.292	−0.563	Moderately Negative
Thailand	−0.299	−0.504	Moderately Negative
Subtotal 9 countries (15.52%)	Average −0.141	Average −0.211	
Panel E. Moderately Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Italy	−0.410	−0.529	Moderately Negative
Greece	−0.521	−0.812	Highly Negative
Spain	−0.544	−0.634	Moderately Negative
France	−0.555	−0.654	Moderately Negative
Portugal	−0.654	−0.713	Highly Negative
Subtotal 5 countries (8.62%)	Average −0.537	Average −0.668	
Panel F. Highly Negative Correlation under CNN			
Country	Corr (CNN)	Corr (MLP)	MLP Classification
Lebanon	−0.732	−0.850	Highly Negative
Algeria	−0.777	−0.770	Highly Negative
Subtotal 2 countries (3.45%)	Average −0.755	Average −0.810	
Overall Summary			
Sample Countries	Average Corr (CNN)	Average Corr (MLP)	
58 countries	0.166	0.184	

Table C1a. Forecast Performance Summary across Correlation Categories

Correlation Category	Model	Average MAE	Average MSE	Average RMSE
Highly Positive	CNN	70.779	7,978.442	72.943
	MLP	52.569	8,231.589	72.508
Moderately Positive	CNN	204.331	281,748.801	211.630
	MLP	184.766	253,339.878	202.634
Weakly Positive	CNN	76.570	36,269.168	79.653
	MLP	81.359	38,951.891	114.172
Weakly Negative	CNN	126.091	64,343.519	129.996
	MLP	125.752	64,550.162	174.577
Moderately Negative	CNN	90.753	22,023.353	105.311
	MLP	103.439	29,266.568	129.099
Highly Negative	CNN	115.553	13,588.148	116.428
	MLP	73.553	14,622.950	110.112

Notes:

- (1) MAE, MSE, and RMSE denote mean absolute error, mean squared error, and root mean squared error, respectively.
(2) All reported statistics represent cross-country average forecasting performance measures within each correlation category.

Table C2. Comparison of Cross-country Linkage Identification across Models

Panel A. Cross-model Identification Results by Predictive Correlation Category

Correlation Category	Sample Countries	CNN	MLP	ARDL	NARDL	FMOLS	NFMOLS
Highly Positive	2	2 (100%)	2 (100%)	0 (0%)	2 (100%)	2 (100%)	2 (100%)
Moderately Positive	23	23 (100%)	23 (100%)	8 (34.8%)	15 (65.2%)	11 (47.8%)	16 (69.6%)
Weakly Positive	17	17 (100%)	17 (100%)	7 (41.2%)	16 (94.1%)	8 (47.1%)	15 (88.2%)
Weakly Negative	9	9 (100%)	9 (100%)	3 (33.3%)	7 (77.8%)	5 (55.6%)	5 (55.6%)
Moderately Negative	5	5 (100%)	5 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Highly Negative	2	2 (100%)	2 (100%)	0 (0%)	1 (50.0%)	0 (0%)	1 (50.0%)

Panel B. Overall Identification Results

Model	Countries Identified	Percentage
CNN	58	100.00%
MLP	58	100.00%
ARDL	18	31.03%
NARDL	41	70.69%
FMOLS	26	44.83%
NFMOLS	39	67.24%

Notes:

(1) Cointegration relationships in the ARDL and NARDL models are determined using the bounds test. For the FMOLS and NFMOLS models, cointegration is assessed based on the combined evidence from the Hansen parameter instability test, Park's added variables test, and the Engle–Granger and Phillips–Ouliaris cointegration tests.

(2) “Model Coverage” refers to the proportion of countries within each correlation category identified by a given model as exhibiting significant comovement with U.S. CDS spreads. For example, 3/4 indicates that, among the four countries within a given category, three are identified by the model as exhibiting significant linkage characteristics.

(3) “Overall Summary” reports the total number and proportion of countries, among all 58 sample countries, identified by each model as exhibiting comovement with U.S. CDS spreads. This summary facilitates comparisons between deep learning models and traditional time-series approaches in identifying cross-country sovereign credit risk linkages.

Appendix Closing Remark

Overall, the appendix results indicate that deep learning models identify substantially broader cross-country sovereign credit risk comovements than traditional time-series approaches. In addition, the robustness analyses based on 3-year and 10-year CDS spreads broadly support the main empirical findings obtained from the benchmark 5-year CDS spreads.