

Investigating the Spillover Effects of UK Sovereign Debt Crisis Risks with Deep Learning Models

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Abstract

This study applies deep learning models to examine the spillover effects of the UK sovereign debt crisis risk at the end of 2022, emphasizing the correlation between the volatility of UK sovereign debt default risks and the sovereign debt credit risks of Eurozone countries. The research objective is to explore whether the sovereign credit default swap (CDS) spreads of the UK during the debt crisis period affect other Eurozone countries. We use the Multilayer Perceptron (MLP) model and Convolutional Neural Networks (CNN) model in neural networks to predict the sovereign credit default swap (CDS) spreads of other Eurozone countries. We then compare these predictions with the actual CDS spreads of those countries to investigate the correlation and explore the relationship between the UK sovereign debt default risks and the sovereign credit risk of other countries. The predictions using those models show that 93.75% to 100% have highly to moderately positive correlations. This demonstrates that the historical daily CDS data from six months before and after the UK debt crisis event days reveal that the sovereign credit risk of Eurozone countries has been profoundly affected by the UK's debt crisis. The primary contribution of this paper lies in the successful application of deep learning models to examine the relevance of sovereign debt default risk spillover.

Keywords: UK sovereign debt crisis, Deep Learning Model, Multilayer Perceptron (MLP) Model, Convolutional Neural Networks (CNN) Model

JEL codes: E50, E60, F33, F34

1. Motivation

The British pound experienced a significant depreciation at the end of September 2022, approaching parity with the euro against the U.S. dollar. The European financial markets were turbulent and uneasy, with particular attention on the substantial sell-off of UK government bonds in the market, sparking concerns about the outbreak of a systemic financial risk crisis. Former U.S. Treasury Secretary Larry Summers, in his speech at the International Institute of Finance (IIF) annual meeting on October 14, 2022, mentioned:

"At present, central banks around the world are raising interest rates to combat inflation, which could lead to a wave of global economic crisis. The recent turbulence in the UK bond market serves as a warning signal."

On September 23, 2022, the UK Treasury unveiled its largest fiscal stimulus plan since 1972. This not only led to a significant increase in bond market supply but also eroded confidence in the UK government's monetary policy, prompting a sell-off of the British pound and UK government bonds. As a result, the Bank of England was compelled to officially announce emergency bond purchases on September 28, 2022, to mitigate market volatility. The underlying causes of the turbulence in the UK bond market include issues related to Brexit, the impact of the Russia-Ukraine war leading to inflation and pushing the UK into a vicious cycle of deflation, economic recession, and fiscal shortages.

The motivation behind this study stems from the recent economic turbulence in Europe, marked by a significant depreciation of the British pound and a substantial sell-off of UK government bonds, raising concerns in the market about the potential

occurrence of a systemic financial crisis. Particularly, data published by the Bank for International Settlements (BIS) reveals that the United States, Spain, France, Japan, Germany, Canada, Switzerland, and Australia have substantial foreign assets exposure to the UK. The United States, in particular, has 30-40% of its foreign assets exposure to Europe originating from the UK.

In other words, if a financial debt crisis were to occur in the UK, it would have a significant global impact. The UK government has implemented various policy measures in an attempt to boost the British economy. Recognizing the high dependence and interconnectedness between many countries' financial systems and the UK, this study aims to explore the impact of a potential debt crisis in the UK on the sovereign credit risk of other nations. Due to data limitations, this paper focuses its investigation on the Eurozone, which shares geographical proximity and deep historical ties with the United Kingdom.

The European Central Bank's annual report for the year 2008, using sovereign credit default swap (CDS) spreads as a measure of national sovereign credit risk, also indicates that countries with poor credit ratings, such as Greece and Spain, show a significant impact of sovereign CDS spreads on credit risk. This suggests that sovereign CDS are one of the most effective financial instruments for hedging against reference asset credit risk. This study adopts sovereign CDS spreads as a proxy for each country's credit risk. The price of sovereign CDS is represented by sovereign CDS spreads, serving as a crucial indicator for measuring credit risk. Numerous studies have found that sovereign CDS spreads possess the ability to rapidly reflect market information.

This paper utilizes historical daily data on CDS spreads in the six months prior and subsequent to the 2022 UK debt crisis event, examining the fluctuations in

sovereign CDS spreads resulting from the crisis in the UK bond market. We reference relevant news announcements related to the 2022 UK bond market crisis from the Bank of England's interest rate decision statements and meeting minutes. We select the initial occurrence point for the 11 event days and move six months backward, as well as the final occurrence point for the 11 event days and move six months forward, to establish the observation period for our study. We aim to examine the impact of the UK government's fiscal and monetary policies and other related measures before and after the occurrence of the UK debt crisis on the sovereign credit risk of other countries.

In contrast to Dooley and Hutchison (2009), who considered whether there was a common response effect among 14 emerging market countries and the magnitude of their responses, our paper primarily examines the volatility of sovereign credit risk in the 16 countries of the Eurozone, exploring the spillover transmission effects and impact of the 2022 UK bond market crisis on the systemic financial risk crisis in Eurozone countries.

This paper focuses on the sovereign credit risk, an aspect that has been relatively underexplored in the current machine learning literature. The aim is to leverage the advantages of deep learning models, known for their proficiency in analyzing vast amounts of data with complex, nonlinear relationships. The objective is to successfully examine the relevance of the spread and diffusion of sovereign credit risk across countries, aiming for improved predictive performance in forecasting sovereign credit risk.

In response to the residual noise, non-linearity, and idiosyncratic characteristics inherent in real-world financial data and information, the optimal strategy is to employ an interdisciplinary approach that combines statistical and machine learning (ML)

algorithms for analysis. Unlike traditional statistical analysis methods, the distinctive feature of machine learning models lies in its ability to handle non-normally distributed data and intricate non-linear relationships in high dimensions. Machine learning models involve the application of suitable algorithms by computer systems through extensive databases, utilizing past historical data and experiences for machine learning and analysis. During this process, predictive models are developed after identifying operational patterns, and they are not limited by the nature of the data (e.g., data categories) or the distribution of the data. When applied appropriately, machine learning models can effectively enhance the accuracy of predictive models. Deep learning model, a subset of machine learning model, involves computer systems autonomously discovering features within extensive databases, generating judgments akin to human decision-making. It is an extension of machine learning model that emerged after 2006, utilizing stacked layers of deep neural networks and new mechanisms for continuous learning from vast data (Hinton and Salakhutdinov, 2006). In recent years, deep learning model has demonstrated its effectiveness in applications such as image recognition, speech recognition, Industry 4.0, smart finance, smart healthcare, intelligent transportation, and smart agriculture. Machine learning model enhances the ability to learn from data, while deep learning model utilizes non-linear computational methods to extract features for learning. Particularly, deep learning models outperform traditional regression models in predictive performance due to their proficiency in analyzing high-dimensional data and complex non-linear relationships between variables, especially when dealing with intricate and non-linear correlations among variables that can impact predictive results (Albanesi and Vamossy, 2019).

The empirical results of this study indicate that all sample countries exhibit positive correlations. The predictions using the MLP model show that 93.75% have a

highly to moderately positive correlation, while the CNN model predictions show a 100% highly to moderately positive correlation. This suggests that the sovereign credit risk of the 16 European countries is profoundly influenced by the events of the UK debt crisis, as observed in the historical daily CDS data from six months before and after all the event days of the UK debt crisis. The primary contribution of this paper lies in the application of deep learning methods, demonstrating their capability to more accurately depict the spillover effects of the UK debt crisis on the sovereign credit risk of Eurozone countries.

2. Literature Review

Machine learning is fundamentally transforming various aspects of our lives. Today, machine learning algorithms can accomplish tasks that were once exclusive to professionals. The financial sector is currently undergoing a moment of revolutionary innovation, redefining the next generation's understanding of money and investment (Lopez de Prado, 2018). Machine learning is a branch of artificial intelligence, and deep learning is a branch of machine learning, as illustrated in Figure 1, depicting the relationship among the three.

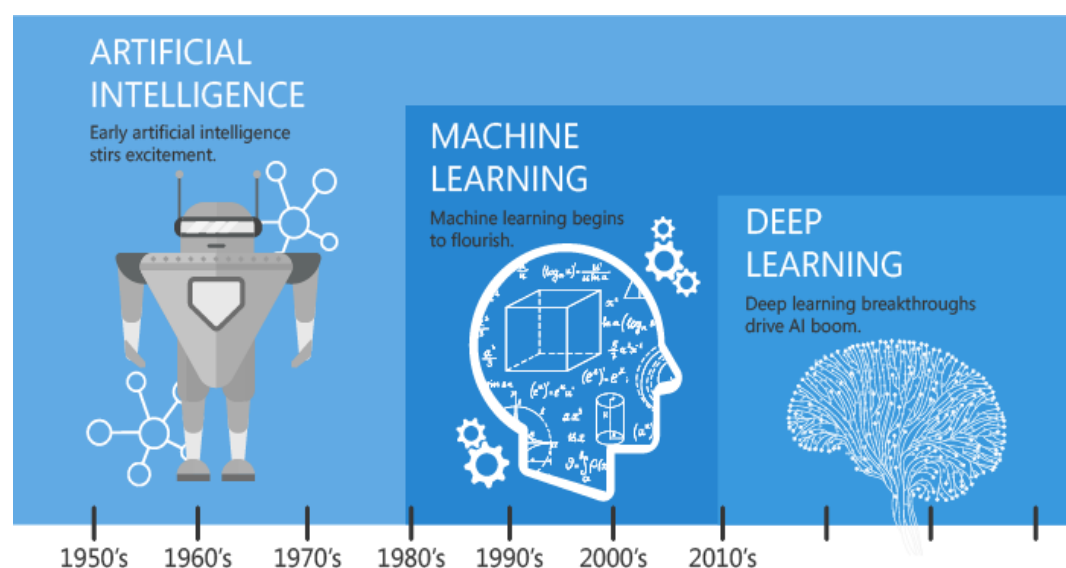


Figure 1. The Relationship between artificial intelligence, machine learning, and deep learning (T.C. Lin, 2020)

Machine learning models are becoming increasingly prevalent in algorithmic trading and investment management. In the financial domain, the challenges it faces include existing theoretical model frameworks and the practical application of models. Simultaneously, there is a necessity to address how to manage the complexities associated with these advanced technologies. Machine learning models have been applied to assess risks in financial institutions, predict bank credit defaults, and construct predictive models for financial crises using neural network models. Other research topics include corporate bankruptcies, medical disease predictions, and more. These studies suggest that machine learning classification methods can address a wider range of issues with higher accuracy compared to traditional statistical methods. In recent years, there has been an increasing citation of deep learning methods in discussing various topics. The frequently cited deep learning methods include multilayer perceptron (MLP), convolutional neural networks (CNN) and deep neural networks (DNN). And the relevant literature are as follows,

Delashmit et al. (2005) discussed the latest advancements in MLP neural networks, highlighting that backpropagation and its related methods are commonly used training techniques, primarily employed for incorporating gradient information. Recent developments include the utilization of Output Weight Optimization-Hidden Weight Optimization (OWO-HWO) technology, significantly enhancing the training and testing performance of MLP.

Ramchoun et al. (2016) proposed a novel approach using genetic algorithms to optimize the architecture of MLP networks. The research results indicate that this new

model demonstrates advantages over previous models in classification problems, exhibiting robust generalization and applicability to real-world problem-solving.

The Convolutional Neural Network (CNN) model is primarily used for handwritten character recognition tasks. It was first proposed by LeCun et al. (1998). The structure includes convolutional layers, pooling layers, and fully connected layers, establishing the foundational architecture of the CNN model through feature extraction. This allows the model to automatically learn the spatial features of images, thereby effectively recognizing handwritten digits and characters.

Liao (2019) proposed an innovative method utilizing Convolutional Neural Networks (CNN) for predicting financial product price trends and formulating trading strategies. This method first converts one-dimensional time series data, such as the opening price, highest price, lowest price, and closing price of financial products over a period of time, into two-dimensional image forms. Then, it uses CNN to extract features from these images, capturing important patterns and features hidden within them. Subsequently, the extracted features are fed into a classifier to predict and classify the future price movements of financial products, achieving effective predictions of future price trends.

Uysal and Mulvey (2021) present an application of machine learning in institutional asset allocation. The framework primarily involves "institutional modeling and forecasting" and "identifying an institution-based strategy" to enhance the performance of risk-parity investment portfolios. Supervised learning algorithms, including random forests based on extensive macroeconomic databases, are employed to estimate the probability of upcoming economic recessions or stock market contractions.

Hansen (2020) delves into how quantitative traders cope with model complexity when developing machine learning-driven trading algorithms through interviews. The analysis reveals that machine learning traders employ the Occam's razor principle as a heuristic tool to prevent excessive model complexity, ensuring a certain level of human control and interpretability in the modeling process. Understanding this approach to handling complexity is crucial for comprehending the contemporary shift in human roles in data and model-driven finance. The study explores a new perspective on the interaction between humans and machine learning models in the field of financial social research.

Odom and Sharda (1990) were among the pioneers, utilizing neural networks to predict loan default risks. Tam and Kiang (1992) also used neural networks to predict bank default risks, comparing accuracy with logistic regression and decision tree methods. Empirical results indicated that neural networks had superior predictive power compared to other methods. Huang et al. (2004) utilized support vector machines and backpropagation neural networks to predict credit ratings, with support vector machines demonstrating better predictive performance.

Petropoulos et al. (2019) applied various machine learning and deep learning models to predict the probability of default for bank borrowers. They utilized gradient boosting models and deep learning neural networks, aiming to reduce data dimensions and enhance the accuracy of predicting future financial data through data mining algorithms. Their goal was to more effectively monitor credit risk in national banking systems. Witten et al. (2016) mentioned four commonly used machine learning techniques, including logistic regression, Naive Bayes, decision trees, and k-nearest neighbors models. A.E. Khandani et al. (2010) employed machine learning methods to construct nonlinear nonparametric models, analyzing consumer credit risk. They found

that machine learning predictions encompassed more diverse information compared to traditional credit scoring prediction methods. Addo et al. (2018) utilized various machine learning and deep learning models to predict the probability of default for bank borrowers. They compared logistic regression, random forest, gradient boosting models, and four types of deep learning neural network models. The study found that decision tree-related models outperformed neural network models. Butaru et al. (2016) used decision trees, random forests, and logistic regression models to predict the performance of credit card industry risk management. They employed machine learning models to predict the default situations of credit card customers using monthly data from six banks from 2009 to 2013.

Caruana and Niculescu-Mezil (2006) and Criminisi et al. (2012) mentioned that over the past decade, random forest models have been successfully applied in empirical out-of-sample prediction classification frameworks. They are considered one of the most creative learning algorithms applicable to various research objectives. Galindo and Tamayo (2000) tested mortgage data to determine defaults, using Classification and Regression Trees (CART) classification method. They compared the results with k-nearest neighbors models, artificial neural networks, and Probit models. Min and Jeong (2009) employed binary classification methods for predicting corporate bankruptcies, including Multi-Discriminant Analysis, logistic regression, decision trees, and artificial neural networks. The study results indicated that binary classification methods can serve as a predictive approach for forecasting corporate bankruptcies.

Barboza et al. (2017) developed a financial variable-based model using machine learning models, including support vector machines, bagging, boosting, and random forests, to predict bank bankruptcies one year before the event occurred. They compared the performance of these models and, on average, found that machine

learning models achieved approximately 10% higher prediction accuracy compared to traditional models. Among them, bagging, boosting, and random forests outperformed other models in predictive performance. Gu, Kelly, and Xiu (2020) conducted a performance comparison of investment strategies for portfolios using various machine learning models, including support vector machines, random forests, linear regression, principal component regression, and neural networks. The study addressed the curse of dimensionality and concluded that neural network predictive models performed well, with shallow neural network models outperforming deep neural network models.

Galindo and Tamayo (2000) utilized machine learning methods to assess credit risk in mortgage loans. Given the inconsistency in previous literature regarding classification problems, they employed traditional statistical probit regression models, CART, artificial neural networks, and K-nearest neighbors (KNN) for testing. They compared the results and found that, in comparison to traditional statistical methods, the model estimation capability of CART was superior. Specifically, the performance of the CART classification and regression tree model surpassed that of the traditional statistical probit regression model.

Richardson et al. (2021) applied various machine learning models for nowcasting New Zealand's GDP, comparing the predictive performance with several traditional statistical models. They employed five machine learning models, including k-nearest neighbors, Boosted Trees (BT), Lasso model (Lasso, Ridge, and Elastic Net, ENET), support vector machines, and neural networks. Comparing the predictive results with several statistical models, they found that machine learning models outperformed, particularly the support vector machines, neural networks, and Lasso model.

Following the literature mentioned above, this paper employs deep learning

methods. Leveraging their advantages in handling complex and non-linear relationships between variables, we aim to achieve accurate predictions of the spillover effects of sovereign credit risk at the national level.

3. Mathematical Model

This study utilizes the commonly used Keras database in Python, combined with Google's developed TensorFlow neural network package. We employ the MLP model and CNN model to explore the magnitude of correlation between predicted values and actual values, thereby illustrating their interrelationship.

A. To predict the risk contagion of sovereign CDS spreads using the MLP model, the key components include:

The **build_model** function defines the structure of the MLP model. It has a simple architecture, including an input layer, two hidden layers with hyperbolic tangent (tanh) activation functions, and an output layer with a linear activation function. The Nadam optimizer is used, and the loss function is mean squared error (MSE).

- Compile the model with the specified learning rate.

MLP Model Architecture :

- Units: Indicates the number of neurons in each hidden layer.
- Activation Function: The hidden layers use the hyperbolic tangent (tanh) activation function, and the output layer has no activation function (linear activation).
- Loss Function: Employing MSE.

Given input data $X \in R^{n \times p}$, where n is the number of samples, and p is the number of input, the MLP model can be expressed as the prediction value $f(X)$:

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

Here, $W_1 \in R^{h \times p}$, $b_1 \in R^h$ represent the weights and bias vector of the first hidden layer, where h is the number of nodes in the first hidden layer, and σ is the activation function. This study adopts the hyperbolic tangent activation function ($\tanh$). The definition process of W_2, b_2, W_3, b_3 is as mentioned earlier, and the detailed breakdown process can be decomposed as in equations (2), (3), and (4).

$$h_1 = \tanh(W_1 \cdot X + b_1) \quad (2)$$

$$h_2 = \tanh(W_2 \cdot h_1 + b_2) \quad (3)$$

$$Y_{\text{pred}} = W_{\text{out}} \cdot h_2 + b_{\text{out}} \quad (4)$$

In this context, X represents the input features, W_1, W_2, W_{out} are weight parameters, and b_1, b_2, b_{out} are bias parameters.

The loss function in the MLP model is expressed using MSE:

$$Loss = \frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2 \quad (5)$$

Where y_i is the true value of the i -th sample, and x_i is the corresponding input feature.

Optimal parameter combinations, including the number of hidden units (h), learning rate (η), and batch size, were obtained through Grid Search. In this hyperparameter tuning process, a nested loop iterated through all possible combinations,

aiming to minimize the loss function. Early Stopping, a regularization technique to prevent overfitting, was implemented with a tolerance parameter (patience) to achieve premature termination. Early Stopping can utilize different monitoring metrics, but in general, validation loss is commonly employed. The basic mathematical model for Early Stopping is as follows:

Let $L^{(t)}$ represent the validation loss of the neural network model in the t -th training iteration. Define a tolerance parameter (patience) denoted as p , such that:

$$L^{(t+p)} \geq L^{(t)} \quad (6)$$

Namely, if the validation set loss does not decrease for a complete set of training iterations for p consecutive times, then terminate the training and obtain the current best model.

This study, in the model compilation process, uses the Nadam optimizer, which combines the concepts of the AdaGrad optimizer and Nesterov momentum. Its formula is expressed as follows: ¹

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \odot m_t \quad (7)$$

Where:

- θ_t : The value of weights/parameters at the t -th iteration.
- η : Learning rate.
- $\hat{v}_t$: First-order moment estimate at time t , combining the concept of AdaGrad.

¹ The Nadam (Nesterov-accelerated Adaptive Moment Estimation) optimization algorithm was introduced by Dozat (2016) in the paper titled "Incorporating Nesterov Momentum into Adam." The relevant literature citation is as follows:

Dozat, T. (2016). Incorporating Nesterov Momentum into Adam. arXiv preprint arXiv:1607.01981.

- m_t : Momentum at time t , combining the concept of Nesterov momentum.
- ϵ : Small constant added for numerical stability, preventing the denominator in the formula from being zero.
- $\odot$: Denotes element-wise multiplication.

Specifically, the calculations of $\hat{v}_t$ and m_t in the Nadam optimizer are as follows:

$$\hat{v}_t = \beta_1 \widehat{v_{t-1}} + (1 - \beta_1) g_t^2 \quad (8)$$

$$g_t = \nabla_{\theta} J(\theta_t) \quad (9)$$

Here, g_t represents the gradient of the loss function J with respect to the weight θ at time t . The loss function J is typically taken as mean squared error or cross-entropy. β_1 is the momentum decay coefficient. Therefore, Nadam combines the self-adjusting learning rate of AdaGrad with the accelerating effect of the Nesterov momentum method.

In accepting the optimal hyperparameter combination, the trained model is applied to test data (**x_test** and **y_test**) to evaluate its performance. Various metrics, including correlation (Corr), mean absolute error (MAE), MSE, and root mean squared error (RMSE), are computed as reference indicators for empirical analysis.

B. The mathematical procedure for predicting debt diffusion of CDS spreads using the CNN model is as follows:

1. Conv1D :

Assume the input data is a one-dimensional sequence x with C channels. Let x_c^l be the input of the c -th channel in the l -th layer, k_c^l be the convolution kernel of the c -th channel, and b_c^l be the corresponding bias term. The convolution operation

of the c -th channel in the l -th layer can then be expressed as:

$$x_c^{l+1}(n) = f(\sum_m \sum_i x_m^l(n+i) * k_c, m^l(i) + b_c^l) \quad (10)$$

Here, m is the index of the input channel, i is the index of the convolution kernel, the function f is the non-linear activation function (ReLU activation function is used in this study), and n is the position index in the output feature map.

2. MaxPooling1D

Let x_c^l be the input of the c -th channel in the l -th layer, $pool_size$ be the size of the pooling kernel, and $stride$ be the stride. The max pooling operation satisfies the following equation:

$$x_c^{l+1}(n) = \max_{0 \leq i < pool_size} x_c^l(stride * n + i) \quad (11)$$

That is, the maximum value within the region of size $pool_size$ is taken as the output.

3. GlobalAveragePooling1D

Let x_c^l be the input feature map of the c -th channel in the l -th layer with a length of L . The global average pooling is then:

$$x_c^{l+1} = \frac{1}{L} \sum_{n=1}^L x_c^l(n) \quad (12)$$

That is, the average value of the entire input feature map is taken as a single scalar value for the output.

4. Dense

Let x^l be the input vector of the l -th layer, W^l be the weight matrix, b^l be the bias vector, f be the non-linear activation function (*tanh* activation function is used in this study), then the operation of the fully connected layer is given by equation (13).

$$x^{l+1} = f(W^l * x^l + b^l) \quad (13)$$

The model has 2 fully connected layers, followed by an output layer without an activation function, serving as the final output.

5. Loss function

The model uses Mean Squared Error (MSE) as the loss function, defined as:

$$L(y, y_{pred}) = \frac{1}{N} \sum_{i=1}^N (y_i - y_{pred_i})^2 \quad (14)$$

Finally, differences between the performance of the MLP and CNN models were tested. The null hypothesis states that the CNN model's predictions are not superior to those of the MLP model, while the alternative hypothesis suggests that the CNN model's predictions are superior to those of the MLP model, expressed as follows:

$$\begin{aligned} H_0: CNN &\leq MLP \\ H_1: CNN &> MLP \end{aligned} \quad (15)$$

Further evaluate the differences between the two methods using a statistical difference test (T-test).

4. Data Description

The event for this study is the late 2022 crisis in the UK bond market, where the UK government implemented various fiscal and monetary policy measures, declaring the event day to announce efforts to boost the UK economy. The event day is defined based on publicly available information sourced from the Bank of England's published interest rate decision statements and meeting minutes. The news event dates are organized as shown in Table 6. Tables 7 and 8 respectively provide data details and sample country information for this study.

All 11 events are announcements related to the Bank of England implementing various policy measures aimed at boosting the UK economy. If the sovereign credit default swap market is an efficient market, then the sovereign CDS spreads should reflect the aggregate of future expected information. The announcement effects of similar nature should be reflected in the sovereign CDS spreads on the first event day. Previous relevant literature has also chosen the first disclosure date as the announcement day. Therefore, for this study, we use the announcement dates of related news events during the 2022 UK bond market crisis as event days. As shown in Table 6, we selected a total of 11 event days. This study compares the sovereign CDS spreads of 16 countries in the Eurozone, examining the volatility of debt default risk before and after these 11 different news announcement events.

This paper utilizes historical daily CDS data from six months before and after the 11 event days during the UK debt crisis as the data period. We refer to the relevant news announcement events during the 2022 UK bond market crisis, as disclosed in the Bank of England's interest rate decision statements and meeting minutes. We selected the initial occurrence point of those 11 events by moving half a year backward from the event day, that's Event 1 (December 16, 2021) in Table 6. The final occurrence point for those 11 events was selected by moving half a year forward from the event day,

that's Event 11 (November 3, 2022) in Table 6. Therefore, the observation period for this study spans from June 16, 2021, to May 3, 2023. We aim to examine the impact of the UK government's fiscal and monetary policy measures and other relevant actions before and after the occurrence of the UK debt crisis on the sovereign credit risk of other countries.

5. Empirical Results

This study takes the impact of the UK debt crisis on the sovereign credit risk of other countries as an example. It explores whether the occurrence of the UK debt crisis at the end of 2022 will affect the sovereign credit risk of other Eurozone countries by examining the UK sovereign CDS spreads relative to Germany. The predictive target is to use the MLP and CNN models in neural networks with four features: the current period, the previous period, the period before that, and the period before that. The model predicts the sovereign CDS spreads of other Eurozone countries and compares them with the actual sovereign CDS spreads of each country. Through this, the study investigates the correlation between the UK Eurozone crisis and the sovereign credit risk of other Eurozone countries.

Table 1 shows the correlation results of predicting the CDS spreads of 16 other countries using the MLP model based on the UK's CDS spreads (arranged by country). Table 2 displays the rankings based on the correlation magnitude from Table 1. The data for each country in Tables 1 and 2 displays as the average of 30 predictions, and this is sufficient to represent unbiased estimates of the predictive results for each country. The Corr is categorized into highly positive correlation (absolute correlation coefficient greater than or equal to 0.7), moderately positive correlation (absolute correlation coefficient ranging between 0.3 and 0.7), and weakly positive correlation

(absolute correlation coefficient less than or equal to 0.3). Using the four-period spread of the UK sovereign CDS spreads as the feature value to predict the sovereign CDS spreads of other countries, there are 9 countries with a highly positive correlation (56.25% of all 16 countries), 6 countries with a moderately positive correlation (37.5% of all 16 countries), and only Cyprus with a weakly positive correlation (6.25%).

We observe highly positive correlations in the debt risk volatility of five Eurozone peripheral countries (GIIPS). Specifically, Greece and Ireland show a highly positive correlation with the UK debt crisis, while Italy, Portugal, and Spain exhibit a moderately positive correlation with the UK debt crisis. This indicates that, compared to financially robust Eurozone countries, these nations, particularly those with less sound fiscal structures, are more susceptible to the impact of news regarding the UK debt crisis, leading to significant fluctuations in their sovereign credit risk.

Additionally, within the Eurozone, core countries, including Belgium, France, Luxembourg, the Netherlands, and West Germany, exhibit a highly significant positive correlation in sovereign credit risk volatility with the UK debt crisis. Except for Luxembourg due to insufficient data and Germany being the benchmark country not discussed, we find that the sovereign credit risk fluctuations of these major founding countries in the Eurozone are closely and significantly correlated with the UK debt crisis, particularly with highly positive correlations observed in Belgium, France, and the Netherlands.

In particular, for Greece in Table 1, besides having a high degree of correlation, we observe that MAE, MSE, and RMSE are all relatively larger compared to other countries. This indicates that Greece's sovereign debt credit risk, during and after the UK debt crisis event, is significantly influenced by various policy declarations and debt-

related news from the UK. As a result, its risk volatility is exceptionally high, leading to a substantial difference between predicted values and actual data. This outcome aligns with the real-world situation, as Greece has persistently remained on the Eurozone watchlist since the 2009 Eurozone crisis due to its severe debt issues. Possible explanations are as follows:

Most Eurozone countries exhibit current account deficits, with Germany and the Netherlands being the only countries with current account surpluses among the major nations. Many Eurozone countries operate on a deficit, borrowing from abroad. Since the inception of the euro as a major international reserve currency, and with the expansion of financial markets and liquidity, the euro has become an excellent mechanism for financial intermediation. Eurozone countries benefit from low borrowing costs due to the euro's role, leading to increased borrowing. The highlighted issues underscore that the lack of necessary policy coordination and structural mechanisms for fiscal integration in the Eurozone results in interconnected government debt problems among member countries, leading to even higher costs.

The above explanation elucidates the interconnected impact of government debt problems between Greece and its main creditor nations, the Eurozone countries. Therefore, if these major creditor nations are influenced by any policy announcements related to the UK debt crisis, it will further contribute to the expanded volatility of Greece's sovereign credit risk.

Originally part of the Eurozone, the United Kingdom has strong historical and economic ties with the Eurozone countries. Despite formally exiting the European Union in January 2020, we observe that the UK debt crisis at the end of 2022 still

influences the debt risk of other Eurozone countries, leading to fluctuations in their sovereign credit risks.

Table 3 presents the correlation results of predicting the CDS spreads of 16 other countries using the CNN model based on the UK's CDS spreads (arranged by country), while Table 4 displays the rankings based on the correlation magnitude from Table 3. Typically, in statistics, a sample size of 30 is considered large, with its mean serving as an unbiased estimate for the model. Following standard statistical practices, this study conducted 30 predictions and compared them with actual data to determine correlations. The average of these 30 correlations represents an unbiased estimate of the model's predictive trend. From Table 4, it is observed that only Finland, Spain, and Slovakia show moderate correlations (accounting for 18.75% of the total 16 countries sampled), while the remaining 13 countries exhibit high correlations (81.25% of the total sample of 16 countries).

Comparatively, the CNN model shows a higher proportion of countries with highly correlated predictions of CDS spreads compared to the MLP model. Overall, all sampled predictions exhibit positive correlations, with the MLP model achieving moderately to highly positive correlations in 93.75% of cases, and the CNN model achieving a high proportion of 100% with moderately to highly positive correlations. Specifically, the CNN model predicts a higher proportion of countries with highly correlated results, indicating that the CDS credit risks of the 16 European countries are significantly influenced by events surrounding the UK's European debt crisis based on historical CDS data from the six months before and after the event.

Table 5 examines the correlation of predicting other countries' CDS spreads based on the UK's CDS spreads, comparing the differences in predictive performance between

the CNN and MLP models. The study investigates whether there are significant differences in predictive effectiveness between the models. The results indicate that at a 1% significance level, the CNN model's predictions significantly outperform the MLP model's predictions for 13 countries. At a 10% significance level, this superiority is observed for 1 country. In empirical terms, out of the 16 countries studied, 14 show statistically significant evidence (87.5% of all 16 countries) that the CNN model's predictions are significantly better than those of the MLP model. Only Austria and the Netherlands do not reject the hypothesis that the MLP model performs equally or better than the CNN model in predicting CDS spreads. Overall, using the CNN model to predict the impact of the UK's European debt crisis appears superior to using the MLP model.

While the sizes of the predictive evaluation indicators MAE, MSE, and RMSE in Table 1 to Table 4 vary, where MAE represents the mean absolute difference, MSE represents the mean square difference, and RMSE represents the square root of the mean square difference, these data reflect the proximity of the predicted values to the actual data. This study emphasizes the post-prediction correlation, indicating the trend between predicted values and actual values. Overall trends show positive correlations with actual predicted CDS risk data for respective countries. Using the MLP model, predictions exhibit a highly positive correlation for 56.25% of countries and a moderately positive correlation for 37.5% of predicted countries. In summary, a remarkable 93.75% of the countries display a moderately to highly positive relationship. In contrast, the CNN model predicts a highly positive correlation of up to 100%. In conclusion, despite the UK's departure from the Eurozone, events like the European debt crisis continue to profoundly impact trade-related countries in Europe. Regarding neural network prediction methods, the CNN model notably outperforms the MLP

model.

In summary, the empirical results of this study indicate that the sovereign CDS spreads of all 16 European countries are significantly affected by the UK debt crisis event. This suggests that the application of deep learning methods in this study indeed provides a more accurate description of the spillover effects on sovereign credit risk.

6. Conclusion

This study applies deep learning models to examine the spillover effects of the UK debt default risk at the end of 2022. We emphasize the correlation between the volatility of UK debt risk and the sovereign credit risk of Eurozone countries. The empirical results indicate that all sampled countries exhibit positive correlations. The MLP model predicts highly to moderately positive correlations in 93.75% of cases, while the CNN model achieves 100% highly to moderately positive correlations. Overall, using the CNN model to forecast the impact of the UK's European debt crisis shows superior performance compared to the MLP model. This suggests that the sovereign CDS spreads of all 16 European countries are significantly influenced by the UK debt crisis event, as observed in the historical CDS data spanning the six months before and after the UK debt crisis event.

This study finds that both the peripheral countries and several wealthier core countries within the Eurozone are affected by the UK debt crisis, exhibiting a highly or moderately positive correlation with the emergence of debt default risk. This aligns with intuition and reflects the current situation, illustrating that despite the UK's withdrawal from the EU, changes in its fiscal policies still impact geographically proximate Eurozone countries with close historical ties and extensive economic and trade relations.

The main contribution of this paper lies in the application of deep learning models, leveraging their strengths in analyzing large volumes of data with complex and non-linear correlations. This allows for a successful examination of the relevance of the spillover diffusion of UK sovereign credit risk and accurately describes the impacts. The future extension of this study will focus on examining the spillover effects on other regional countries, especially those with higher holdings of UK debt. We will investigate whether there is a significant correlation between the sovereign credit risk of these countries, heavily exposed to the UK, and the UK debt default events, beyond the Eurozone.

Table 1 Correlation of CDS Spreads Prediction from the UK to Other Countries using MLP Model (Sorted by Country)

Country	Corr	MAE	MSE	RMSE
Austria	0.815761	0.797757	1.244024	1.067468
Belgium	0.866731	1.137733	2.095192	1.441132
Cyprus	0.202191	8.138802	77.726357	8.814445
Estonia	0.600848	3.809106	21.895128	4.654202
Finland	0.498678	2.753754	13.308793	3.535679
France	0.827244	0.830533	1.325045	1.098156
Greece	0.783311	19.329204	664.657757	25.387617
Ireland	0.723102	1.253211	2.845009	1.662657
Italy	0.543220	6.814214	73.316986	8.540245
Latvia	0.857703	7.801670	94.636221	9.679538
Lithuania	0.866677	8.614350	133.234659	11.509957
Netherlands	0.770044	0.933326	1.751194	1.295310
Portugal	0.472025	5.412267	44.924064	6.675597
Slovakia	0.486252	3.978501	21.396677	4.616432
Slovenia	0.740334	4.654681	32.651686	5.681412
Spain	0.435676	5.030546	40.259512	6.281744

Note: The data for each country above represents the average of 30 executions.

Table 2 Correlation of CDS Spreads Prediction from the UK to Other Countries using MLP Model (Sorted by correlation magnitude)

	Country	Corr	MAE	MSE	RMSE
Highly positively correlated $ Corr \geq 0.7$	Belgium	0.866731	1.137733	2.095192	1.441132
	Lithuania	0.866677	8.61435	133.2347	11.50996
	Latvia	0.857703	7.80167	94.63622	9.679538
	France	0.827244	0.830533	1.325045	1.098156
	Austria	0.815761	0.797757	1.244024	1.067468
	Greece	0.783311	19.3292	664.6578	25.38762
	Netherlands	0.770044	0.933326	1.751194	1.29531
	Slovenia	0.740334	4.654681	32.65169	5.681412
	Ireland	0.723102	1.253211	2.845009	1.662657
Subtotal	9 countries (56.25%)	Average 0.805656			
Moderately positively correlated $0.7 > Corr > 0.3$	Estonia	0.600848	3.809106	21.89513	4.654202
	Italy	0.543220	6.814214	73.31699	8.540245
	Finland	0.498678	2.753754	13.30879	3.535679
	Slovakia	0.486252	3.978501	21.39668	4.616432
	Portugal	0.472025	5.412267	44.92406	6.675597
	Spain	0.435676	5.030546	40.25951	6.281744
Subtotal	6 countries (37.5%)	Average 0.506117			
Weakly positively correlated $ Corr \leq 0.3$	Cyprus	0.202191	8.138802	77.72636	8.814445
Subtotal	1 country (6.25%)	Average 0.202191			
Total	16 countries (100%)	Average 0.655612			

Note: The data for each country above represents the average of 30 executions.

Table 3 Correlation of CDS Spreads Prediction from the UK to Other Countries using CNN Model (Sorted by Country)

Country	Corr	MAE	MSE	RMSE
Austria	0.805167	0.537973	0.907438	0.949564
Belgium	0.881305	1.019267	2.306594	1.516625
Cyprus	0.784027	4.430366	37.173056	6.093287
Estonia	0.719740	2.593245	11.284201	3.354171
Finland	0.665539	2.004423	6.838934	2.613510
France	0.848641	0.564481	0.782263	0.884001
Greece	0.887835	12.733723	380.149677	19.492287
Ireland	0.738830	1.006490	2.459738	1.568192
Italy	0.734698	4.894544	39.633725	6.289314
Latvia	0.878491	5.858060	67.910697	8.236879
Lithuania	0.901101	6.863678	96.382833	9.813634
Netherlands	0.714107	0.850512	1.621824	1.273166
Portugal	0.702191	4.123664	29.260201	5.406373
Slovakia	0.651046	3.366230	16.615373	4.073000
Slovenia	0.855096	3.374637	21.174931	4.596889
Spain	0.664734	3.659683	22.944674	4.788396

Note: The data for each country above represents the average of 30 executions.

Table 4 Correlation of CDS Spreads Prediction from the UK to Other Countries using CNN Model (Sorted by correlation magnitude)

	Country	Corr	MAE	MSE	RMSE
Highly positively correlated $ Corr \geq 0.7$	Lithuania	0.901101	6.863678	96.382833	9.813634
	Greece	0.887835	12.733723	380.149677	19.492287
	Belgium	0.881305	1.019267	2.306594	1.516625
	Latvia	0.878491	5.858060	67.910697	8.236879
	Slovenia	0.855096	3.374637	21.174931	4.596889
	France	0.848641	0.564481	0.782263	0.884001
	Austria	0.805167	0.537973	0.907438	0.949564
	Cyprus	0.784027	4.430366	37.173056	6.093287
	Ireland	0.738830	1.006490	2.459738	1.568192
	Italy	0.734698	4.894544	39.633725	6.289314
	Estonia	0.719740	2.593245	11.284201	3.354171
	Netherlands	0.714107	0.850512	1.621824	1.273166
	Portugal	0.702191	4.123664	29.260201	5.406373
Subtotal	13 countries (81.25%)	Average 0.803941			
Moderately positively correlated $0.7 > Corr > 0.3$	Finland	0.665539	2.004423	6.838934	2.613510
	Spain	0.664734	3.659683	22.944674	4.788396
	Slovakia	0.651046	3.366230	16.615373	4.073000
Subtotal	3 countries (18.75%)	Average 0.660440			
Total	16 countries (100%)	Average 0.777034			

Note: The data for each country above represents the average of 30 executions.

Table 5 Hypothesis Testing for Differences in Correlation of Predicting CDS Spreads from the UK to Other Countries (Sorted by Country)

Country	Corr(CNN)	Corr(MLP)	CNN-MLP	t-value (p-value)
Austria	0.805167	0.815761	-0.010593	-1.234784 (0.886589)
Belgium	0.881305	0.866731	0.014574	2.577244 (0.007655)***
Cyprus	0.784027	0.202191	0.581835	51.579073 ($p < 10^{-6}$)***
Estonia	0.719740	0.600848	0.118892	12.676221 ($p < 10^{-6}$)***
Finland	0.665539	0.498678	0.166861	17.339377 ($p < 10^{-6}$)***
France	0.848641	0.827244	0.021397	2.914126 (0.003403)***
Greece	0.887835	0.783311	0.104524	16.420930 ($p < 10^{-6}$)***
Ireland	0.738830	0.723102	0.015728	1.663202 (0.053522)*
Italy	0.734698	0.543220	0.191478	13.753081 ($p < 10^{-6}$)***
Latvia	0.878491	0.857703	0.020788	5.340346 (0.000005)***
Lithuania	0.901101	0.866677	0.034424	7.619114 ($p < 10^{-6}$)***
Netherlands	0.714107	0.770044	-0.055937	-5.807730 (0.999999)
Portugal	0.702191	0.472025	0.230166	18.618108 ($p < 10^{-6}$)***
Slovakia	0.651046	0.486252	0.164793	11.669087 ($p < 10^{-6}$)***
Slovenia	0.855096	0.740334	0.114762	14.815048 ($p < 10^{-6}$)***
Spain	0.664734	0.435676	0.229058	24.867245 ($p < 10^{-6}$)***

Note: The data for each country above represents the average of 30 executions. ($H_0: CNN \leq MLP$; $H_1: CNN > MLP$)

Table 6 The definition of events

Event	Definition	Event day	Description
Event 1	The UK raised interest rates by 15 basis points to 0.25%, halted additional bond purchases, and maintained the total size of the Asset Purchase Facility (APF).	2021/12/16	The Bank of England raised interest rates.
Event 2	The UK raised interest rates by 25 basis points to 0.5%	2022/2/3	The Bank of England raised interest rates.
Event 3	The UK raised interest rates by 25 basis points to 0.75%	2022/3/17	The Bank of England raised interest rates.
Event 4	The UK raised interest rates by 25 basis points to 1.0%, and is expected to begin selling its £20 billion corporate bond holdings in September. The plan aims to complete the sales no later than early 2024, with the selling pace subject to adjustments as needed.	2022/5/5	The Bank of England raised interest rates.
Event 5	The UK raised interest rates by 25 basis points to 1.25%, and has initiated a passive reduction of its government bond holdings. Approximately £32 billion worth of government bonds, set to mature in July of this year, will not be reinvested.	2022/6/16	The Bank of England raised interest rates and announced a balance sheet reduction (shrink the balance sheet)
Event 6	The UK raised interest rates by 50 basis points to 1.75% and is expected to begin actively shrinking its balance sheet starting in September. The actual scale and operational details will be determined in the September meeting.	2022/8/4	The Bank of England raised interest rates.

Table 6 Continue

Event	Definition	Event day	Description
Event 7	The UK raised interest rates by 50 basis points to 2.25% and announced an active balance sheet reduction starting on October 3. The balance sheet will be reduced by £80 billion over the next year, bringing the holdings of government bonds down to £758 billion.	2022/9/22	The Bank of England raised interest rates and announced an active balance sheet reduction(shrink the balance sheet)
Event 8	The Ministry of Finance announces a mini-budget including tax cuts and energy subsidies plan.	2022/9/23	Fiscal stimulus plan
Event 9	In response to the government's announcement of tax cuts and concerns over rising yields and market volatility, the Bank of England has announced a temporary bond-buying plan. The central bank will purchase long-term bonds within the period from September 28 to October 14, with no predetermined size, and the balance sheet reduction will be postponed until October 31.	2022/9/28	The Bank of England's Emergency Purchase Programme, postponing balance sheet reduction
Event 10	The Ministry of Finance announces the withdrawal of the income tax bracket plan.	2022/10/3	Relevant fiscal policies
Event 11	The UK raises interest rates by 75 basis points to 3.0%.	2022/11/3	The Bank of England raised interest rates.

Source: Bank of England, the central bank of the United Kingdom, whose monetary policy primarily aims to control inflation. It holds interest rate meetings several times a year, with decisions made through a vote by the nine-member committee. The interest rate decision statement and meeting minutes are released simultaneously. This study quotes information from their published news releases.

Table 7 Data Description

Data	Definition	Source	Period
Sovereign Debt Default Risk (proxied by Sovereign CDS spreads)	CDS (Sovereign credit default swaps, 5-year dollar denominated CDS) (We deduct the CDS spreads of all sample countries uniformly, excluding the benchmark country Germany.)	Datastream	2021/6/16 ~ 2023/5/3

Table 8 Sample Countries

Region	Number	Countries
Periphery countries	5	Greece, Ireland, Italy, Portugal, Spain
Other countries	11	Austria, Belgium, Cyprus, Finland, France, Netherlands, Slovakia, Slovenia, ESTONIA, Latvia, Lithuania
Benchmark country	1	Germany
Total	17	

The Eurozone is a region consisting of European Union member countries that use the common currency 'Euro.' Currently, there are 19 countries in the Eurozone, including Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain. Due to the absence of Luxembourg and Malta in the Datastream database, this study's sample data includes 17 countries. We deduct the CDS spreads of all sample countries uniformly, excluding the benchmark country Germany. Therefore, a total of 16 sample countries are observed.

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