

Britaly? Identifying euro area historical analogues to the UK's 2022 bond market shock

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Abstract

Comparing the UK's 2022 sovereign debt crisis with earlier European examples is crucial for a holistic understanding of how such crises emerge and evolve to better comprehend the warning signs of sovereign distress and the importance of coherent and credible economic governance. Both crises were marked by sudden and severe shifts in investor confidence. The UK government's "mini budget" announcement on September 23, 2022, sent yields on UK gilts soaring at a daily rate not seen since the 1990s. Similarly, official disclosure by Papandreou's government regarding the actual state of Greece's public finances on October 20, 2009, caused daily sovereign debt yields in some euro area countries to rise to levels not seen since joining the euro. The primary objective of this paper is to conduct a comparative econometric analysis of the euro area sovereign bond market, with the goal of identifying past episodes similar to the turmoil experienced in the UK government bond market during September–October 2022. This comparative perspective aims to provide valuable insights for future crisis prevention in an increasingly interconnected global financial system. Specifically, we use daily data on 10-year government bond yields from January 3, 2000, to June 30, 2023, and apply both univariate and multivariate nearest neighbours' techniques. We also introduce a novel methodology, *k*-Related Simultaneous Nearest Neighbours (*k*-RSNN), which offers significant advantages over traditional forecasting models such as ARIMA and GARCH (it enables simultaneous analysis of multiple sovereign bond markets, effectively capturing cross-country dynamics, detecting nonlinear patterns and structural breaks, and identifying past events similar to recent crises). Our results show that financial markets initially interpreted the UK bond market disruptions between October 17 and 31, 2022, as comparable to the fiscal credibility crises faced by Spain and Italy during the European sovereign debt crisis. However, after the Bank of England's targeted intervention, perceptions of the UK's fiscal credibility shifted toward alignment with core euro area countries. Finally, from January 16 to June 30, 2023, we find strong parallels with the sovereign-bank risk nexus that previously affected Spain and Italy during the euro area crisis. Our findings indicate that although the origins of the crisis in the UK and the euro area are different (lack of fiscal credibility and poor communication vs. solvency concerns, weak banking systems, and limitations of incomplete economic unions), examining them together offers valuable lessons: policymakers should better recognise early warning signs of sovereign distress and reinforce the importance of coherent and credible economic governance.

Keywords: Financial crisis, Bond markets, Fiscal credibility, United Kingdom, Analogies, Nearest neighbours' analysis.

JEL Codes: C22, G14, H30, H61.

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1. Introduction

The credibility of budgetary pronouncements has become increasingly crucial to sovereign debt markets. Private expectations may deviate from official statements if fiscal policy targets are reported to be unachievable or unreasonable. A still recent and glaring example: the response of the United Kingdom (UK) sovereign bonds market to the government's announcement in September 2022 of measures that could have dramatically increased the deficit and the level of public debt (Bank of England, 2023), has motivated the analysis presented in this paper.

This bond market turmoil is significant for several reasons. First, it highlighted the critical importance of fiscal credibility and clear communication with markets, even for advanced economies with strong credit ratings. Second, studying this episode provides valuable insights into how financial markets react to policy and investor confidence shifts, offering policymakers lessons on managing fiscal credibility and ensuring market stability. Third, understanding the dynamics of the 2022 UK turmoil helps develop early-warning systems for future crises, improving financial market resilience. Finally, the analysis of this event offers broader implications for the global bond market, as similar stress events could emerge in other countries facing economic uncertainty, making it a crucial case study for the analysis of sovereign debt markets and the impact of fiscal policies on market behaviour. In this respect, comparing the UK's 2022 debt crisis with earlier European cases helps explain how such crises begin and evolve, highlighting the role of sudden shifts in investor confidence and rapid changes in market sentiment.

In this context, the main objectives of this paper are the following. Firstly, to contribute to the scant existing empirical literature on this issue by testing whether Mrs Truss's announcement undermined the credibility of the UK fiscal policy in the bond markets. And secondly, to fill a notable gap in the literature by providing a novel methodology (the k -Related Simultaneous Nearest Neighbours approach) to analyse and compare sovereign bond market stress across countries, focusing on the UK's 2022 bond market turmoil. Previous studies on sovereign bond market crises often focus on individual countries or employ traditional time-series models (like ARIMA or GARCH), which typically treat countries in isolation and fail to capture the cross-country dynamics and systemic interdependencies that are central to understanding market stress during episodes like the 2022 UK crisis. Conversely, this paper contributes to the literature by conducting a comparative econometric analysis of the euro area bond market, aiming to identify past events similar to the UK gilt market volatility in September–October 2022.

Therefore, since the episode of loss of credibility and confidence in financial markets¹ caused by the UK government's statement in September 2022 revived the spectre of the euro area's sovereign debt crisis and the UK's sovereign markets turmoil was even compared with that experienced by peripheral countries (particularly in Italy) of the euro area by some analysts (The Economist, 2022), we think that the proposed k -RSNN technique that allows to look for analogous episodes in the past of the UK government bond yield series and of their peers in the euro area, inferring that events occurring at different times can be comparable in certain aspects if they share similarities, is appropriate in our analysis. The ability to identify such analogies, as well as the diversity and number of events used for comparison largely determines the effectiveness of these historical analogies. So, by leveraging this robust, non-parametric approach to examining past situations, identifying pertinent comparisons, and improving the methods of selecting analogies (which is a second methodological contribution of this study), we aim to gain significant insights into the upheaval in UK government bonds in 2022, ultimately enhancing our understanding of this critical event.

Moreover, the euro area offers a helpful comparison for analysing the UK's 2022 bond turmoil due to shared inflationary pressures, interest rate hikes, and market volatility. UK pension funds were hit hard by liability-driven investment strategies, a practice also seen in parts of the euro area. The Bank of England's bond-buying intervention mirrored past European Central Bank actions, while political and fiscal uncertainty further fuelled instability, similar to sovereign debt challenges in some euro area countries. Additionally, while the UK's bond market is highly liquid, smaller euro area economies often face liquidity constraints. Comparing these factors helps assess whether the UK's crisis was unique or part of broader global trends. Moreover, Italy and Spain are valuable points of reference for the UK's 2022 bond turmoil due to their experiences during the European sovereign debt crisis (2009–2012), when both faced severe market stress, rising bond yields and fiscal sustainability concerns. Like the UK, they share structural features such as high government debt and exposure to market speculation. During the euro area crisis, Spain, and Italy experienced sovereign-bank risk nexuses, similar to UK market concerns. Their histories provide key context for assessing how fiscal policy shifts and interventions shape sovereign bond markets.

The findings of this paper offer valuable insights for market participants, regulators, and policymakers. By identifying historical analogues to recent UK bond market disruptions, the k -

¹ It led to a significant repricing of the UK's financial assets, particularly affecting long-dated government debt, leading to a substantial risk to the financial stability of the UK (Financial Policy Committee, 2022). The Bank of England (BoE) action and the subsequent correction of this announcement stopped the immediate negative consequences, though.

RSNN methodology provides a tool for detecting early signs of fiscal credibility risks and sovereign-bank linkages before they escalate, allowing investors to adjust risk pricing strategies and asset allocations based on parallels with past euro area crises and helping them make informed decisions. Additionally, regulators can use lessons from Spain and Italy's sovereign debt crisis to design effective intervention strategies, as demonstrated by the Bank of England's role in stabilising market perceptions. Since k -RSNN enables simultaneous comparison of multiple sovereign bond markets, policymakers can develop coordinated responses to systemic financial risks, improving crisis management. Furthermore, the research highlights vulnerabilities in fiscal credibility and sovereign bank nexuses, guiding long-term reforms that enhance financial stability and resilience. These insights improve risk anticipation, strengthen intervention strategies, and foster stability in sovereign debt markets.

The remainder of this paper is as follows. Section 2 offers a brief literature review. Section 3 describes the data and methodology. Section 4 reports the results of our analysis, and Section 5 concludes. The Appendices describe several statistical procedures used in the article, present alternative methods and their results, and report additional outcomes based on other commonly used measures of predictive accuracy in the empirical literature.

2. Literature Review

Discrepancies can arise between private expectations and official statements when fiscal policy objectives are viewed as unrealistic or fiscally unsustainable. This could cause uncertainty in the evolution of expectations regarding the government's capacity to ensure fiscal sustainability, risking the stability of the country's debt market [see Bi *et al.* (2013), End (2023) or Barbier-Gauchard *et al.* (2023)].

Nevertheless, limited research has examined the impact of fiscal announcements on sovereign risk. However, some exceptions exist. De Mendonça and Nicolay (2017), Montes and Acar (2020), and Montes *et al.* (2022) centre their analysis on the case of Brazil. Falagiarda and Gregori (2015) focus their study on the Italian sovereign debt market, whilst Li *et al.* (2023) examine the Chinese bond market. Although they employ varying methodologies and analyse different countries, all this empirical research emphasises that the impact of budgetary declarations on sovereign risk is contingent upon their credibility (see Beetsma *et al.*, 2009).

This paper aims to contribute to the scant empirical literature on this issue by testing whether Mrs Truss's announcement in 2022 undermined the credibility of the UK fiscal policy in the bond markets through the lens of the innovative methodology k -RSNN, which allows us to compare the UK's 2022 sovereign debt crisis with earlier European debt crisis episodes.

Concretely, the fundamental idea of the k -RSNN technique is to select past episodes of the time series related to the one we want to analyse assuming that sovereign bond markets learn from their peers in similar economic circumstances (see Chahine and Chidambaran, 2023), and making use of memory's selective and reconstructive abilities to highlight the most "salient" elements (Fischhoff *et al.*, 1977). Consequently, by contrast with traditional time-series models (like ARIMA or GARCH), the k -RSNN methodology offers a non-parametric and flexible approach that simultaneously compares multiple sovereign bond markets, making it uniquely suited to identifying historical analogues and nonlinear patterns during periods of fiscal and financial stress.

However, while ARIMA or GARCH methodologies have been broadly used in the empirical literature to examine sovereign market behaviour [see Del Brio *et al.* (2014), De Santis and Stein (2015), Pires *et al.* (2017), Bouri *et al.* (2019), Cifarelli and Paladino (2020), and Campos-Martins and Amado (2022), to name a few], to our knowledge, there are no applications of the k -RSNN approach to sovereign debt market evolution to date. Nevertheless, there are many study fields, including renewable energy (Hu *et al.*, 2014; Zhou *et al.*, 2020) and transportation (Cai *et al.*, 2020), where the k -NN algorithm has proven to be effective.

Indeed, the existing research on RSNNs indicates their suitability for modelling complex temporal patterns inherent in financial data in areas such as high-frequency trading, volatility forecasting, multimodal data integration, or for capturing intricate temporal dependencies. However, in the field of finance, although machine learning techniques have been widely used in recent years [see, e.g., Aziz *et al.* (2022), Cakici *et al.* (2023), and Zhao *et al.* (2023)], the NN algorithm is still scarcely used [Fernández *et al.* (1999), Kanas (2003), and Andrada *et al.* (2016) are some of the exceptions].

Therefore, the k -RSNN methodology proposed in this paper to analyse sovereign bond markets behaviour provides a comparative perspective that is, not only essential for developing a comprehensive understanding of how such crises originate, evolve, and impact financial markets, but it may also yield valuable insights for anticipating and mitigating future sovereign debt crises in an increasingly interconnected global financial system.

Certainly, both the European sovereign debt crisis and the UK's debt turmoil were marked by abrupt and pronounced shifts in investor confidence, highlighting the speed and volatility with which market sentiment can deteriorate in response to perceived fiscal and policy risks. Concretely, the UK government's "mini budget" announcement on September 23, 2022, triggered a sharp spike in gilt yields, the steepest daily increase since the 1990s (see Ilzetzki, 2024). Similarly, the official disclosure by Prime Minister Papandreou's government on October

20, 2009, revealing the accurate scale of Greece’s fiscal imbalances, led to a surge in sovereign bond yields across several euro area peripheral countries, reaching levels not seen since the adoption of the euro (see Gómez-Puig and Sosvilla-Rivero, 2014).

Their origins were different, though: lack of fiscal credibility and poor communication vs. solvency concerns, weak banking systems, and limitations of incomplete economic unions. However, examining them together, as this paper proposes with a new methodology, offers valuable lessons: policymakers should better recognise early warning signs of sovereign distress and reinforce the importance of solvent and credible fiscal and economic governance.

3. Data and methodology

3.1 Data and preliminary analysis

We utilise daily 10-year government bond yield data gathered from the Refinitiv database for the United Kingdom and eleven euro area countries, both core countries (Austria, Belgium, Finland, France, Germany, and The Netherlands) and peripheral economies (Greece, Ireland, Italy, Portugal, and Spain).

Our data runs from January 3, 2000, to June 30, 2023². This period is relevant to the analysis of the 2022 UK bond turmoil since it includes the European sovereign debt crisis and the so-called “diabolic loop” or “sovereign-banking” nexus in Europe.

The debt crisis can be dated from October 20, 2009, when Greece’s government publicly acknowledged that its public finances were in far worse shape than previously reported (that exposed deep-rooted structural problems in Greece’s fiscal management and triggered a broader crisis across the euro area) until July 26, 2012, when ECB President Mario Draghi pronounced three magic words: he was going to do “whatever it takes” to preserve the euro. These words marked the turnaround of the euro crisis since they expressed a strong commitment to Europe and the euro area.

Moreover, the outbreak of the sovereign debt crisis in Europe revealed that its origin went more profound than the fiscal imbalances in euro countries. The interconnection between private and public debt (see Singh *et al.*, 2016), and thus between banking and sovereign crises, was obvious

² The original period spans 8,562 days, including weekends. To focus on regular business activity, Saturdays and Sundays are excluded, resulting in a reduced sample of 6,130 weekdays (Monday through Friday). This adjusted series still includes public holidays; in such cases, the value from the preceding day in the original series is imputed to maintain continuity. No outlier removal was performed. For the implementation of the k -NN and k -RSNN predictors, min-max normalisation is applied to the data. This technique rescales each feature to the [0, 1] range by linearly transforming values based on their observed minimum and maximum, ensuring consistency in the distance-based similarity search. For the UK, the LSTM model employs logarithmic differencing to achieve stationarity in the time series. Prior to forecasting, the differenced data are standardised to have zero mean and unit variance, which enhances numerical stability and facilitates model training. After predictions are made in this standardised domain, they are transformed back to the original scale through a combination of de-standardisation and exponentiation.

and became especially evident “during” and “after” the European sovereign debt crisis (see Gómez-Puig and Sosvilla-Rivero, 2023). Some authors (see Dell’Ariccia *et al.*, 2018) offer a detailed account of the numerous pathways that result in a “sovereign-banking nexus”, where the financial well-being of banks and sovereigns was intertwined. The concern over the emergence of a vicious cycle in which sovereign fragility would endanger the asset side of the banks’ balance sheet was one cause for this increasing interconnectedness. In turn, bank distress would boost sovereigns’ explicit and implicit bailout costs, imperil public budgets, and cast doubt on the sustainability of their debt (see, for instance, Alter and Schüler, 2012).

We first analyse the pairwise correlation coefficients between the series under study. Our results (Figure 1) suggest the existence of a pattern linking, on the one hand, the United Kingdom and core euro area economies and, on the other, peripheral euro area countries between them.

[Insert Figure 1 here]

To investigate this finding more thoroughly, we look for clusters in the sovereign markets in our sample to group countries that share the same characteristics. The more notable the differences between the groups (i.e., the more prominent the inter-cluster distances) and the larger the similarities within a group (i.e., the smaller the intra-cluster distances), the more distinct the clustering is.

To that end, we first employ Principal Component Analysis (PCA) to project the high-dimensional dataset onto a lower-dimensional subspace (typically two or three components). PCA is a preprocessing technique to transform the original set of possibly correlated variables into a reduced set of uncorrelated components (referred to as principal components) that capture the maximum variance in the data. This dimensionality reduction facilitates more efficient modelling while preserving the essential structure of the dataset and mitigating potential multicollinearity issues (see Johnson and Wichern, 1992). Table 1 shows the results.

[Insert Table 1 here]

As can be seen, PC1 accounts for a substantial 79.5% of the total variance in the dataset and reflects a strong common core factor within the euro area. Most Western and Northern European countries are closely grouped along this component, while Greece and Portugal diverge significantly, suggesting structural uniqueness or economic divergence from the core model. PC2 explains an additional 17.7% of the variance and serves to differentiate a subset of countries (the euro area periphery) from the rest. Finally, PC3 captures an additional 1.11% of the variance, representing meaningful, idiosyncratic variation not explained by the first two components. This

suggests that Spain and Italy deviate from both the core and peripheral groups, exhibiting distinct patterns of behaviour.

To enhance the visual exploration of the data structure and enable the identification of potential clusters, we employ a scatter plot representation of the two and three main principal components (Figures 2 and 3). As shown in Figure 2, we identify two groups within the euro area corresponding to the central (Austria, Belgium, Finland, France, Germany and the Netherlands) and peripheral (Greece, Ireland, Italy, Portugal and Spain) countries³. However, when incorporating the third principal component (Figure 3), Spain and Italy emerge as a distinct group, separate from the other peripheral countries. This suggests the presence of two peripheral clusters within the euro area: an outer peripheral group (Greece, Ireland, and Portugal) and an inner peripheral group (Spain and Italy). Similar clustering results were obtained using the *K*-means clustering method based on vector quantisation⁴, with the advantage that the application of PCA for clustering could help to overcome several limitations of the *K*-means algorithm, including sensitivity to initial conditions, the curse of dimensionality, and challenges in handling noisy data while preserving the correlation structure among the variables.

[Insert Figures 2 and 3 here]

To simplify the presentation of the results of the predictions obtained for the *k*-RSNN predictors, we will present them for the three groups of countries in the sample identified by the data apart of the UK: Austria, Belgium, Finland, France, Germany and the Netherlands; Italy and Spain; and Greece, Ireland and Portugal.

3.2. The Nearest Neighbours analysis.

Scholars in economics and finance, market traders, and the general public often analyse current events by drawing parallels with historical data, a process complicated by the vast, noisy, and unstructured nature of available time series. The Nearest Neighbour (NN), one of the most fundamental classical algorithms in supervised machine learning techniques, can be used to address regression and classification issues, helping to find these commonalities.

The NN forecasting approach presents some advantages over competing approaches. First, it eliminates the need to create a specific econometric model to represent time series data. Instead, it suggests that short-term predictions can be made based on historical trends. Second, it works by identifying segments of the past time series that closely resemble the most recent segment available before the observation we want to predict (see, e.g., Stone, 1977; Cleveland, 1979 and

³ The existence of fragmentation in the euro area sovereign bond markets has also been emphasised by Candelon *et al.* (2022) and Costola and Iacopini (2023).

⁴ These additional results are not shown here to save space, but they are available from the authors upon request.

Hardle and Linton, 1994). Third, the proposed approach goes beyond the Box-Jenkins (BJ) methodology. While BJ models rely on analysing correlations between lagged data and error terms to extend previous values into the near future, NN methods select relevant past observations based on their levels and geometric patterns, rather than their chronological placement. And, finally, one of its most important attributes is that the NN algorithm performs very well asymptotically. In simple terms, for a large design set, the expected probability of incorrect classification (error) P achievable with k -NN is bounded as follows:

$$P^* \leq P < 2P^*$$

where P^* represents the optimal (minimal) error rate for a given underlying distribution (see Cover and Hart, 1967).

Consequently, in scenarios with limited or no prior knowledge of data distribution, the NN algorithm serves as a simple yet effective non-parametric classifier that demonstrates resilience to noisy data and is straightforward to implement (see, e.g., Devroye and Wagner, 1977; and Devroye et al., 1994). It operates within supervised classification by utilising the class labels found in the training data and relies on similarity metrics to categorise new data instances while preserving the characteristics of existing instances in the dataset⁵. Essentially, k -NN classifies new data based on the collective classifications of its nearest neighbours, making it a method that primarily depends on the proximity of data points within the feature space.

3.2.1. Univariate k -NN forecasting analysis

k -NN is a widely used algorithm in time series forecasting, appreciated for its simplicity and intuitive approach to identifying similar instances within large-dimensional feature spaces (Andrada-Félix et al., 2003). It also demonstrates robustness when dealing with high-dimensional and incomplete data (Lin et al., 2012). In many cases, k -NN performs nearly as well as the optimal classifier (see, e.g., Wilson, 1972). The k -NN algorithm operates on the principle that past time series sequences are likely to resemble future sequences. To generate forecasts using k -NN, similar patterns of behaviour are identified through nearest neighbours, and their development over time is utilised to produce the forecast (Kanas, 2003).

The k -NN regression is based on learning by comparing the given test sample with the training dataset, and it can be formally defined as follows:

Let $\{x_t\}_{t=1}^T$ be a finite time series. Segments with comparable dynamic behaviour are carefully selected to find geometric patterns in the time series, and these segments are then utilised to

⁵ For a comprehensive review of the k -NN algorithm, refer to the work of Syriopoulos *et al.* (2023).

forecast the next term in the series (i.e., x_{T+1}). The fundamental idea behind applying k -NN to time series forecasting is that since all time series have recurring patterns, we can identify earlier, comparable patterns to the current series structure and use those patterns to forecast future behaviour. Therefore, we consider vectors $x_t^{m,\tau}$, of m observations sampled from the original time series at intervals of $\tau \in \mathbb{N}$ units:

$$x_t^{m,\tau} = (x_t, x_{t-\tau}, \dots, x_{t-(m-1)\tau}), \quad t = 1 + (m-1)\tau, \dots, T \quad (1)$$

with m referred to as the *embedding dimension* and τ called the *delay parameter*. These m -dimensional vectors are often called m -histories, while the m -dimensional space $\mathbb{R}^m$ is referred to as the phase space of time series. For the sake of simplification, we can consider only the case of $\tau = 1$, so we can write $x_t^{m,\tau} = x_t^m$. Let $\{x_t^m, x_{t+1}^m\}_{t=m}^{T-1}$ be a training dataset with $T - m$ samples, where $x_t^m \in \mathbb{R}^m$ is an input sample from m -dimensional space and its target value is $x_{t+1} \in \mathbb{R}$. We can identify k -NN in the dynamic behaviour of two segments in the time series x_t based on the proximity of two m -histories in the phase space $\mathbb{R}^m$. To establish the search of NNs to a new test sample x_T^m , we look for the closest k vectors in the phase space $\mathbb{R}^m$, in the sense that they minimised a distance metric:

$$d_t(x_t^m, x_T^m), \quad t = m, m+1, \dots, T-1 \quad (2)$$

The choice of the smoothing parameter, k , determines how flexible the k -NN approach is (Hu *et al.*, 2014). To assess the similarity between the state vector x_t^m and the current state vector x_T^m in the training dataset, the Euclidean distance is commonly used in k -NN regression (Altman, 1992).

Next, we consider the set of k m -histories:

$$x_{t_1}^m, x_{t_2}^m, \dots, x_{t_k}^m \quad (3)$$

most similar according to the increasing in (2). Finally, we consider predictors of the future evolution of x_T^m . Let $\hat{x}_{T+1}$ be a predictor of x_{T+1} . This forecast can be obtained as some adequate average or median of the target values $x_{t_1+1}, x_{t_2+1}, \dots, x_{t_k+1}$ after to the k -NNs chosen (Biau *et al.*, 2012; Györfi *et al.*, 2002), the usual k -NN regression estimate takes the form:

$$\hat{x}_{T+1} = \frac{1}{k} \sum_{j=1}^k x_{t_j+1} \quad (4)$$

Figure 4 shows a representative graphical depiction of the k -NN analysis.

[Insert Figure 4]

Applying k -NN to univariate time series is grounded in the assumption that data generated by stable underlying processes often exhibit recurring patterns over time. When a historical segment of the series displays a trajectory similar to that of the current observation window, the subsequent evolution of that past segment can serve as an empirical basis for forecasting the short-term future dynamics of the series. This approach leverages the notion that structural similarities in past and present patterns may reflect comparable underlying mechanisms or external conditions.

Unlike conventional time series models such as ARIMA and GARCH, which tend to prioritise recent data for short-term prediction, our innovative approach harnesses the power of relevant information from past episodes that accurately reflect the present. This allows us to extract insights from even the most remote historical events, ensuring a more comprehensive and effective prediction method. Adopting this broader perspective improves accuracy and allows us to make informed comparisons of significant events based on a more complete understanding of past trends. In this vein, some studies have demonstrated that our expectations about some macroeconomic variables such as inflation are profoundly influenced by experiences that can last for years, even stretching across generations, highlighting the importance of understanding how historical factors shape our perceptions and responses to economic changes (Malmendier and Nagel 2016; Braggion *et al.* 2023; and Gagnon and Kamin, 2025, among others).

3.2.2. Multivariate k -RSNN forecasting analysis.

As noted above, our methodological contribution is based on extending k -NN predictors to a multivariate context, enabling the selection of nearest neighbours for a given time series using information from a broader set of related simultaneous time series. In particular, we propose a novel method called k -Related Simultaneous Nearest Neighbours (k -RSNN) technique. Similar behavioural patterns in terms of simultaneous nearest neighbours are located in other “explanatory” related series to generate k -RSNN-based forecasts, and their temporal evolutions are exploited to generate the forecast in the time series under study. The notion of k -RSNN can be formally defined as follows:

Given one finite time series $\{x_t\}_{t=1}^T$ and, to simplify notation, let us consider a set of two related time finite series: $\{y_t\}_{t=1}^T$ and $\{z_t\}_{t=1}^T$. In generating the out-of-sample forecast in the time series x_{T+1} , based on other series y_t, z_t , we simultaneously consider k -NNs in related series. To

establish the search of simultaneous k -NNs to last available m -history for the time series $x_T^m \in \mathbb{R}^m$, we look for the closest k vectors in the vectorial space $(y_t^m, z_t^m) \in \mathbb{R}^{2m}$ that minimise the function:

$$d_t(y_t^m, x_T^m) + d_t(z_t^m, x_T^m), \quad t = m, m+1, \dots, T-1 \quad (5)$$

In this way, we obtain a set of k associated simultaneous m -histories in both related series:

$$y_{t_1}^m, y_{t_2}^m, \dots, y_{t_k}^m \quad (6)$$

$$z_{t_1}^m, z_{t_2}^m, \dots, z_{t_k}^m \quad (7)$$

according to the increasing in (5). The forecast $\hat{x}_{T+1}$ can be obtained as some adequate average or median of the target values of the subsequent to the k -associated simultaneous m -histories in both related series chosen to forecast in the time series being analysed.

Figure 5 visually illustrates the method, and Table 2 presents the corresponding step-by-step procedure for the k -RSNN.

[Insert Figure 5 and Table 2 here]

Therefore, the fundamental idea of the k -RSNN technique is to select past episodes of the time series related to the one we want to analyse assuming that sovereign bond markets learn from their peers in similar economic circumstances (see Chahine and Chidambaran, 2023), and making use of memory's selective and reconstructive abilities to highlight the most "salient" elements (Fischhoff *et al.*, 1977). The approach aligns with the sticky information hypothesis (Mankiw and Reis, 2002), which posits that economic agents adjust their expectations and decisions based on older information rather than immediately incorporating new data due to the costs associated with acquiring and processing information. It is also consistent with the rational inattention hypothesis (Sims, 2003), which suggests that agents have limited information-processing capacity and allocate their resources to process only the most relevant information.

3.2.3. Improving the selection of analogies

An additional methodological contribution of this paper is to improve the analogy selection process.

Min-max normalisation is one of the most widely used strategies for data scaling in k -NN-based techniques (Shalabi *et al.*, 2006), guaranteeing a fast generalisation through distance-based learning and ensuring that larger values do not overwhelm smaller ones in different financial episodes.

Metric learning aims to measure the similarity or dissimilarity between objects based on samples with a distance metric for learning tasks. Nevertheless, as k -NN approaches have been shown to perform better when employed with a learnt appropriate distance metric from a sample instance, ideally, each application needs a unique customised distance metric (Weinberger and Saul, 2009). Since the k -NN algorithm relies on the computation of distances for its search process, mastering an appropriate distance metric can significantly enhance this regression approach's performance. In matrix form, a variety of distance metrics can be stated as:

$$d_{ij}(x_i^m, x_j^m) = \sqrt{(x_i^m - x_j^m)^t M (x_i^m - x_j^m)} \quad (8)$$

where $x_i^m, x_j^m \in \mathbb{R}^m$ and M is a $m \times m$ dimension matrix. Note that we retrieve the Euclidean distance when M is the identity matrix. This paper focuses on the Mahalanobis distance metric, which provides a well-studied and successful framework for distance metric learning (see Suárez *et al.*, 2021, for a recent survey). Using the inverse of the covariance matrix, $M = \Sigma^{-1}$ the Mahalanobis distance takes into account the covariance structure on the k -NNs between the training sample and test sample correlation.

3.3. Alternative forecasting methods

To emphasise the power and novelty of the proposed k -RSNN approach, we compare its performance with a broader class of established methods applied to the same task. Specifically, we employ the autoregressive integrated moving average (ARIMA) model combined with the generalised autoregressive conditional heteroskedasticity (GARCH) model, as well as the long short-term memory (LSTM) network.

The hybrid ARIMA-GARCH time series model integrates ARIMA's linear forecasting capabilities with GARCH's ability to model time-varying conditional variance. This model may perform well in capturing volatility clustering but might be less effective at identifying nonlinear relationships or capturing more complex data patterns. It has become a classic approach in financial time series analysis, being widely used to study the volatility and co-movements of sovereign bond yields, particularly during periods of market stress (see, e.g., Tsuchida *et al.*, 2014; and Silvapulle *et al.*, 2016). Appendix 1 outlines the key features of the ARIMA-GARCH model.

The LSTM network represents a leading approach for forecasting in financial time series analysis. As a type of artificial neural network (ANN), LSTM is specifically designed for modelling sequential data and can effectively capture long-term dependencies in time series prediction (Greff *et al.*, 2017). Initially proposed by Hochreiter and Schmidhuber in 1997, the

LSTM architecture was developed to address the challenges posed by vanishing and exploding gradients, which often lead to numerical instability during training (Bengio *et al.*, 1994). At its core, the LSTM framework features a memory cell that preserves information across varying time spans, together with three nonlinear gates (input, output, and forget gates) that control the movement of information into, within, and out of the cell (see Appendix 2; Yu *et al.*, 2019, for further details). These deep learning models, despite their potential for higher accuracy, are often regarded as “black box” models, which complicates the interpretability of their results and the understanding of the underlying drivers of market behaviour.

3.4. Evaluation Metrics

In empirical studies, different criteria can be used to evaluate the out-of-sample performance of forecasting models. In this paper, we assess the predictive accuracy of the estimated models using several standard statistical metrics: root mean square error (RMSE), the mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), Theil inequality coefficient (TIC), and mean directional accuracy (MDA). These metrics measure the difference between predicted and actual values, with lower (greater) values indicating greater (lower) predictive accuracy and a closer (farther) alignment between forecasts and observed outcomes (for MDA). These metrics measure the difference between predicted and actual values, with lower (greater) values indicating greater (lower) predictive accuracy and a closer (farther) alignment between forecasts and observed outcomes (for MDA).

We define two sample periods for analysis: an estimation period (in-sample) and a forecasting period (out-of-sample). The in-sample period comprises T observations, ending on the last day of each episode identified in the UK government bond yield series. Specifically, the in-sample period spans from January 3, 2000, to October 14, 2022, for the forecast period October 17–31, 2022; from January 3, 2000, to October 31, 2022, for the forecast period November 1, 2022–January 13, 2023; and from January 3, 2000, to January 13, 2023, for the forecast period January 16–June 30, 2023. The corresponding out-of-sample horizons consist of $H = 11, 54$, and 120 days, respectively, and serve as the test datasets. In the prediction period, one-step-ahead forecasts are considered, where $h = 1, \dots, H$. Given the values of the actual observation of the time series at time $T+h$ $h = 1, \dots, H$ and the future forecast for that observation $\hat{x}_{T+h}$, $h = 1, \dots, H$, the evaluation metrics are defined as follows:

$$\begin{aligned}
RMSE &= \sqrt{\frac{1}{H} \sum_{h=1}^H (\hat{x}_{T+h} - x_{T+h})^2} \\
MAE &= \frac{1}{H} \sum_{h=1}^H |\hat{x}_{T+h} - x_{T+h}| \\
MAPE &= \frac{100}{H} \sum_{h=1}^H \left| \frac{\hat{x}_{T+h} - x_{T+h}}{x_{T+h}} \right| \\
SMAPE &= \frac{100}{H} \sum_{h=1}^H \frac{|\hat{x}_{T+h} - x_{T+h}|}{(|\hat{x}_{T+h}| + |x_{T+h}|)/2} \\
TIC &= RMSE / \left(\sqrt{\frac{1}{H} \sum_{h=1}^H \hat{x}_{T+h}^2} + \sqrt{\frac{1}{H} \sum_{h=1}^H x_{T+h}^2} \right) \\
MDA &= \frac{1}{H} \sum_{h=1}^H I[(\hat{x}_{T+h} - x_{T+h-1})(x_{T+h} - x_{T+h-1})]
\end{aligned}$$

4. Empirical results

We start by looking for historical analogies of the behaviour of the UK government bond yield with embedding dimension $m=16$ corresponding to the period between September 23 (announcement of the polemic “mini budget” that involved £45bn of annual, unfunded tax cuts, equal to 1.8% of GDP) and October 14, 2022 (cessation of Kwasi Kwarteng, the British chancellor). Figure 6 shows the most similar past episodes identified in the UK government bond yield series based on detected analogies in the corresponding series for Italy and Spain (where most of such analogies are concentrated) for the forecast period October 17 - 31, 2022, when the Bank of England (BoE) started a targeted intervention⁶. Then, based on these analogies, we predict the UK government bond yield one step ahead during this first period of interest in our forecast analysis⁷. Figure 7 displays the RMSE of forecasts generated by an ARIMA and GARCH model estimated on the UK government bond yield time series, by k -NN and k -RSNN predictors (for each group of analogies) and different numbers of k , and by multiple vanilla LSTM models⁸, while Appendix 3 shows the results obtained using other measures of predictive

⁶ The corresponding figures showing the most similar past episodes detected in the corresponding series for the rest of the groups are not shown here to save space, but they are available from the authors upon request.

⁷ Due to information rigidities, market participants often take time to fully reflect the information contained in official announcements (Ricco *et al.*, 2016). Moreover, Cimadomo *et al.* (2016) emphasise how the credibility of fiscal programs affects both forecasts of government bond spreads and how the spreads evolve.

⁸ We employ multiple vanilla LSTM models, with hyperparameters manually tuned to improve network performance. Prior to training, the dataset was standardised to have zero mean and unit variance. Once the LSTM models produced forecasts, the predicted values were rescaled to their original scale through inverse standardisation. For the one-step-ahead forecasting task, the standardised data were split into training and testing subsets. Following the same procedure used for the k -RSNN predictors, the first T observations (ending on the last day of each episode identified in the UK government bond yield series) were used for training. The subsequent H observations, where $H = 11, 54$, and 120 days, were allocated for out-of-sample evaluation, respectively. During training, input sequences of $m = 16, 27$, or 81 consecutive (lagged) time steps were constructed, corresponding to each forecasting episode identified in the UK government bond yield series. The LSTM models were implemented using MATLAB (2023a)'s Deep Learning Toolbox. Model training was guided by the mean squared error (MSE) loss function, and optimisation was performed using the Adam algorithm (Kingma and Ba, 2014) with its default parameters. To mitigate overfitting, a dropout rate of 50% was applied, which yielded robust results across all

goodness commonly used in the empirical literature (MSE, MAE, MAPE, SMAPE, TIC, and MDA).

[Insert Figures 6 and 7 here]

As shown in Figure 7 and Appendix 3, the forecast based on analogies identified in the past behaviour of Italy and Spain outperforms all other forecasts, indicating that these analogies contain additional information not captured by alternative models, including the traditional (linear) ARIMA-GARCH and LSTM forecasting models. This informational contribution suggests that the dynamics embedded in the historical patterns of the Italian and Spanish 10-year government bond yields identified by the (nonlinear) k -RSNN predictors carry relevant signals about the future trajectory of UK government bond yields, signals that are not fully reflected in the UK's own lagged data. Accordingly, the detected analogies enhance predictive accuracy by patterns that anticipate movements in the UK bond market during the forecast period. While this does not necessarily imply a causal relationship in a strict sense, it does reflect a statistical dependency that can be effectively leveraged for forecasting purposes, thereby underscoring the relevance of the proposed k -RSNN predictors.

Figure 8 presents a histogram showing the yearly distribution of episodes in the historical behaviour of Italy and Spain, as identified by the k -RSNN predictors, that are most analogous to the dynamics of the UK bond market during the first analysed period. As can be seen, the majority are concentrated during the euro area sovereign debt crisis (2009-2012). This finding may suggest that the market associated the episode under analysis with the loss of credibility experienced by Spain and Italy during the European debt crisis (see, e.g., European Central Bank, 2013; Falagiarda and Gregori, 2015; McMenamin *et al.*, 2015), particularly amid the heightened sovereign debt tensions of mid-2012. These tensions were fuelled by growing doubts about governments' commitment to resolving the crisis and implementing European Union-level agreements. Investor concerns over Spain's and Italy's failure to align national economic policies with the stability criteria required for monetary union membership contributed to sharp increases in risk premiums and a widening of sovereign bond yield spreads in July 2012. The perceived lack of decisive policy action further undermined confidence, intensified financial market stress, deteriorated financing conditions, and threatened the flow of credit to the real economy. The analogies detected between both episodes are consistent with Melosi *et al.* (2024), who contend that announcing a substantial fiscal stimulus may unintentionally transmit

forecasting horizons (Srivastava *et al.*, 2014). Each network was trained for up to 100 epochs with 50 hidden units. Due to the random initialisation of weights and biases in the LSTM architecture, identical inputs may yield varying outputs across runs. Therefore, the final reported results, depicted in the corresponding figures, summarise the average forecasts and the empirical uncertainty bands, represented by the 5th and 95th percentiles computed over 100 independently trained models with identical configurations.

government concerns about the depth of a recession to the private sector, potentially reducing the effectiveness of policy in stabilising the economy and that such signalling effects arise mainly when the stimulus exceeds expectations and are especially pronounced in times of more significant economic uncertainty. In this context, most UK economists viewed deficit reduction as essential to restoring government credibility following the fiscal turmoil triggered by the September 2022 “mini budget” (Ilzetzki and Jain, 2022). Similarly, during the European debt crisis, many European countries initiated significant austerity measures, often backed by international institutions.⁹

[Insert Figure 8 here]

Subsequently, we consider September 23-October 31, 2022 ($m=27$). Figure 9 depicts analogous past episodes identified in the UK government bond yield series in central euro area countries (where the majority of analogies are found) for the forecast period November 1, 2022-January 13, 2023, when BoE entirely ended the emergency measures. Based on them, we forecast the UK government bond yield one step ahead. Figure 10 presents the RMSE for each of the forecasting models under consideration: univariate k -NN models with varying k values, ARIMA-GARCH models, and LSTM models applied to the UK time series, as well as those from the k -RSNN predictors, evaluated using different sets of analogies and a range of k values. Appendix 4 provides additional measures of prediction accuracy.

[Insert Figures 9 and 10 here]

As can be observed in Figure 10 and Appendix 4, the forecast based on the analogies detected by the k -RSNN predictors in the past behaviour of core euro area countries performs superiorly relative to all other forecasts, revealing a statistical association of these historical episodes and the behaviour of the UK 10-year government bond yields during the forecast period, an association that can be effectively exploited for predictive purposes. This finding may indicate that the market perceived the United Kingdom as having regained the level of credibility traditionally associated with those core euro area countries.

Figure 11 shows a histogram displaying the yearly distribution of analogies identified in the historical behaviour of core euro area countries that help improve the prediction of the UK bond market during the period from November 1, 2022, to January 13, 2023. As can be seen, these analogies are primarily concentrated in the 2013-2015 period, coinciding with the gradual decline in perceived credit and sovereign risk in core euro area countries following the measures implemented in 2012 to address the euro area sovereign debt crisis. This pattern reflects a

⁹ See Anzoategui (2022) for an analysis of how austerity measures affect sovereign spreads.

renewed rise in investor confidence, improved financial market sentiment and financing conditions, and ongoing reform efforts in core euro area economies, which led to notable improvements in both macroeconomic and fiscal fundamentals. It also points to progress toward a more robust framework for economic governance and a gradual strengthening of the euro area's overall macroeconomic outlook.

[Insert Figure 11 here]

Finally, we consider the period between September 23, 2022, and January 13, 2023 ($m=81$). Figure 12 shows the most similar past episodes identified in the UK government bond yield series on analogies in the corresponding series for Italy and Spain (where most of the analogies are detected) for the forecast period January 16-June 30, 2023, which is the end of our sample. Based on these analogies detected in each group described above, we forecast the UK government bonds one step ahead in this last period. Figure 13 displays the RMSE values corresponding to each of the forecasting models evaluated, while Appendix 5 provides additional measures of prediction accuracy.

[Insert Figures 12 and 13 here]

As can be seen in Figure 13 and Appendix 5, the forecast based on the similarities found in Italy's and Spain's historical behaviour beat all other forecasts. This could suggest that the successive banking crises recorded at the beginning of 2023 (see, e.g., Cipriani *et al.*, 2024) would have recalled the interconnection between bank and sovereign risks, which acted as an amplifying mechanism of the European sovereign debt crisis (see, e.g. Alter and Beyer, 2014; or Gomez-Puig *et al.*, 2019).

Figure 14 shows a histogram illustrating the annual frequency distribution of the episodes identified in the historical behaviour of Italy and Spain as most closely resemble the evolution of the UK government bond market during this third analysed period. Notably, the majority of these episodes are concentrated in the years preceding the onset of the euro area sovereign debt crisis (2005-2009). Between 2005 and 2009, the euro area experienced significant changes in fiscal conditions (Eyraud *et al.*, 2017), particularly in Italy and Spain, where governments lacked sufficiently concrete and credible strategies to effectively address their fiscal imbalances. Early in the period, these countries missed their fiscal targets, exceeding the 3% GDP deficit threshold due to weak consolidation efforts and structural imbalances. The improvements observed in 2006 and 2007 were largely cyclical, driven by strong growth and extraordinary revenues rather than sustained policy reform. However, the global financial crisis that began in 2007 reversed these gains. In 2008, euro area governments adopted coordinated measures to stabilise the banking system and support the economy, including stimulus packages and interventions in the financial

sector, particularly in Italy and Spain. As a result, deficits widened in these countries, and public debt increased significantly (see European Central Bank, 2009). By 2009, their fiscal situation had deteriorated dramatically due to the economic recession, rising public spending, and declining revenues, exceeding the thresholds, with a broad-based increase in debt ratios, highlighting the need for credible medium-term fiscal strategies to restore sustainability and market confidence.

[Insert Figure 14 here]

Figures 7, 10, and 13, along with those in Appendices 3, 4, and 5, indicate that the k -RSNN models consistently outperform the ARIMA-GARCH and LSTM benchmarks, based on the average values of predictive accuracy metrics widely used in the empirical literature. This performance advantage is apparent across all episodes identified in the UK government bond yield series, using out-of-sample evaluation datasets with forecast horizons of $H = 11, 54$, and 120 days, underscoring the k -RSNN models' effectiveness and robustness in financial forecasting.

Table 3 presents the runtimes of the alternative prediction algorithms. Combining these results with those presented above regarding predictive goodness, we can contend that despite their higher computational cost relative to traditional models such as ARIMA, the k -NN and especially the k -RSNN predictors offer substantial advantages that justify their use in forecasting applications (particularly in complex or nonlinear time series like government bond yields). These analogy-based methods leverage historical patterns in a flexible, data-driven manner, enabling them to capture structural breaks, regime changes, and heterogeneous behaviours more effectively than parametric models. The k -RSNN framework extends the traditional k -NN by incorporating multivariate analogies and a refined selection mechanism, which consistently improves predictive accuracy across multiple forecast horizons. While their runtime is indeed longer (approximately 9 to 10 times that of ARIMA), this is a reasonable trade-off when the goal is robust, high-quality predictions in real-world, high-stakes settings. As computational resources become increasingly accessible, the time-cost gap becomes less critical, especially considering the gains in forecast reliability and adaptability offered by these models. In short, k -NN and k -RSNN predictors represent a compelling alternative to both conventional approaches, such as ARIMA-GARCH models and deep learning models, like LSTM networks. They combine interpretability, adaptability, and strong predictive performance, which could be particularly valuable when forecasting under uncertainty or structural instability.

[Insert Table 3 here]

5. Concluding remarks

Comparing the UK’s 2022 sovereign debt crisis with earlier cases, such as the European sovereign debt crisis (2009-2012), is essential for a comprehensive understanding of how such crises originate and unfold. It also helps identify early warning signs of sovereign distress and underscores the importance of coherent and credible economic governance. At the same time, although the underlying causes differed (the UK’s crisis was driven by a sudden loss of fiscal credibility and poor communication, whereas the European crisis stemmed from deeper structural issues, including concerns over solvency, fragile banking systems, and the institutional shortcomings of an incomplete economic union), both were marked by abrupt and severe shifts in investor confidence. These cases illustrate how rapidly market sentiment can deteriorate, regardless of the specific trigger, when trust in economic management is undermined.

In this context, this paper aims to conduct a comparative econometric analysis of the euro area sovereign bond market to identify historical episodes that resemble the market turmoil experienced in the UK government bond market during September–October 2022. By adopting a comparative lens, the study seeks to derive insights that can inform the early detection and prevention of future crises within an increasingly interconnected global financial system. To this end, we utilise daily data on 10-year government bond yields from January 3, 2000, to June 30, 2023. The analysis employs both univariate and multivariate nearest neighbours’ techniques, introducing a novel methodology (*k*-Related Simultaneous Nearest Neighbours, *k*-RSNN) that offers notable advantages over traditional models, such as ARIMA and GARCH, as well as deep learning models like LSTM, which have shown promise in analysing sequential financial data, particularly in capturing nonlinear relationships and managing large datasets. Due to its effectiveness in modelling long-range dependencies and complex temporal dynamics, LSTM serves as a strong benchmark for evaluating the forecasting performance of the proposed *k*-RSNN predictors. However, LSTM models can be computationally demanding to train and evaluate, especially when applied to long sequences or large-scale datasets.

Particularly, the *k*-RSNN technique identifies past episodes in the time series that closely resemble the one under analysis, based on the assumption that sovereign bond markets respond not in isolation but by drawing on collective experience from similar economic contexts. This approach leverages the selective and reconstructive nature of memory to highlight the most “salient” historical patterns. Unlike traditional time-series models such as ARIMA or GARCH, *k*-RSNN is a non-parametric and highly flexible method that enables the simultaneous comparison of multiple sovereign bond markets. This makes it particularly well-suited to

detecting nonlinear dynamics, structural breaks, and identifying historical analogues during episodes of fiscal and financial stress.

However, while ARIMA and GARCH models have been widely employed in the empirical literature to analyse sovereign bond market dynamics, to our knowledge, the k -RSNN methodology has not yet been applied to the study of sovereign debt market evolution. Nonetheless, existing research on related nearest neighbours' techniques highlights their effectiveness in modelling complex temporal structures in financial data, particularly in areas such as high-frequency trading, volatility forecasting, multimodal data integration, and the identification of intricate temporal dependencies. Indeed, despite the growing adoption of machine learning methods in finance, nearest neighbour (NN) algorithms remain underutilised in this field. Notable exceptions include studies by Fernández *et al.* (1999), Kanas (2003), and Andrada *et al.* (2016), which demonstrate the potential of NN approaches in capturing non-linear patterns and improving predictive performance. This gap in the literature underscores the value of exploring k -RSNN within the context of sovereign bond markets, especially given its flexibility and ability to accommodate cross-country comparisons during periods of financial stress. The k -RSNN approach is not only instrumental in developing a more comprehensive understanding of how sovereign debt crises originate, evolve, and affect financial markets, but it also holds significant potential for anticipating and mitigating future episodes of sovereign distress. In an increasingly interconnected global financial system, such a perspective is crucial for enhancing early warning capabilities and informing more effective policy responses. The proposed k -RSNN predictor outperforms both traditional linear models, such as ARIMA-GARCH, and advanced nonlinear machine learning approaches, including LSTM networks. Its superior performance stems from its ability to capture complex temporal dependencies. Additionally, the k -RSNN predictor is more computationally efficient and requires less hyperparameter tuning compared to LSTM models.

As far as we know, this is the first paper that analyses the loss of credibility in UK bond markets using the k -RSNN methodology. Our results corroborate the existence of analogues between both crises since they indicate that, in the immediate aftermath of the UK bond market disruptions between October 17 and 31, 2022, financial markets perceived the episode as analogous to the fiscal credibility crises previously experienced by Spain and Italy during the European sovereign debt crisis. However, following the Bank of England's targeted intervention, market perceptions shifted significantly, aligning the UK more closely with core euro area economies regarding fiscal credibility. In the subsequent period, from January 16 to June 30, 2023, we identify strong parallels with the sovereign-bank risk nexus that had previously

amplified market stress in Spain and Italy, highlighting the persistent relevance of interconnected financial and fiscal vulnerabilities in shaping sovereign risk dynamics.

Our results indicate that, although the crises in the UK and the euro area stemmed from different underlying causes, examining them in parallel offers valuable insights. Most notably, the comparison highlights the critical importance of early recognition of sovereign distress signals and reinforces the imperative for policymakers to uphold coherent, transparent, and credible economic governance. Such measures are essential to maintaining investor confidence and mitigating the risk of sudden and destabilising shifts in market sentiment.

Moreover, our findings are also consistent with a growing body of empirical literature which, using a range of methodologies and country cases, has demonstrated that the impact of fiscal announcements on sovereign risk is highly contingent on their perceived credibility [see De Mendonça and Nicolay (2017), Montes and Acar (2020), Montes *et al.* (2022), Falagiarda and Gregori (2015), Li *et al.* (2023) or Melosi *et al.* (2024)]. These findings raise concerns about potential deviations in fiscal policy from what is announced, as such discrepancies pose significant risks to the financial sector. A vulnerable sovereign situation ultimately translates into a vulnerable financial system.

Accordingly, the results of our analysis are in line with the reform of the Stability and Growth Pact (SGP)¹⁰ in European Union (EU) countries which, following a temporary suspension in March 2020 due to the pandemic, was reactivated on December 21, 2023, when the EU Council announced an agreement on a new framework for macroeconomic coordination and fiscal adjustment in EU countries (see EU Council, 2023)¹¹, which came into effect on April 30, 2024. This reform introduced a differentiated approach for each member country, acknowledging the diversity of fiscal positions, public debts, and economic challenges across the EU, and not only the application of rigid budget rules (many authors, Blanchard *et al.* (2021) among them, had been requiring it). Moreover, the current reform not only sends a strong message about the need for high-quality public finances but also underscores the importance of transparency and credibility in the fiscal framework for participants in the financial markets. Summing up, [see Zettelmeyer, (2023) or Menguy (2024)], the new framework sends a powerful signal about¹²: (1)

¹⁰ The Stability and Growth Pact (SGP) is a set of rules designed to ensure that countries in the European Union pursue sound public finances and coordinate their fiscal policies. It was established in 1997, reformed during the **euro area** crisis of the 2010s, and suspended in March 2020 to allow countries to spend as much money as needed to fight the crisis induced by the COVID-19 pandemic. However, the SGP has been reactivated since December 2023.

¹¹ <https://data.consilium.europa.eu/doc/document/ST-15874-2023-REV-4/en/pdf>

¹² The new SGP also aims to help ensure that consolidation efforts are less pro-cyclical and more realistic than they have been to date. In this sense, Hauptmeier and Kamps (2022) acknowledge that the old SGP's rules gave rise to a pro-cyclical bias that hampered its implementation in a low-growth and inflation environment such as the post-COVID period, and Bökemeier and Wolski (2022) show that fiscal policy behaviour turned from a formally pro-cyclical design prior to the

the importance of transparency and credibility to financial markets; (2) the necessary quality of public finances; and (3) the indispensable balance between common rules and national ownership. Indeed, as many authors have pointed out (see End, 2023), maintaining stability in sovereign and financial markets relies more on market participants' trust that policymakers will fulfil their mandates or declared fiscal goals rather than on overly ambitious yet implausible fiscal objectives.

Our methodological contribution is essential for developing a more holistic understanding of how financial crises emerge and evolve. By enabling researchers and market participants to identify patterns and historical parallels in financial time series, the approach facilitates deeper insights into the dynamics of market behaviour. In doing so, it enhances the ability to detect early warning signals of potential distress, thereby supporting more informed decision-making and risk management in increasingly complex financial environments. Besides, it reinforces the critical role of credible fiscal announcements by policymakers, as their impact on sovereign risk is highly dependent on how market participants perceive them.

A natural extension of the analysis presented in this article would be to perform a systematic examination of the most analogous episodes detected to better characterise the patterns obtained. Specifically, our analysis identifies three distinct phases in the behaviour of the UK bond market that closely parallel developments in euro area sovereign debt markets during the crisis period. First, during the period from October 17 to 31, 2022, UK gilt market dynamics closely resembled those of Spanish and Italian sovereign bond markets at the height of the euro area crisis (2009–2012), particularly in terms of investor reactions to deteriorating fiscal credibility. Second, from September 28, 2022, to January 16, 2023, following the Bank of England's targeted intervention, the evolution of UK gilts more closely aligned with the behaviour observed in core euro area sovereign markets (e.g., Germany and France) between 2013 and 2015. And third, in the period from January 16 to June 30, 2023, UK bond market behaviour mirrored that of Spanish and Italian sovereign markets during the pre-crisis years (2005–2009), when the growing interdependence between sovereign risk and banking sector vulnerabilities (the so-called sovereign-bank nexus) emerged as a key source of financial market stress. Conducting a thorough examination of the most analogous episodes will provide invaluable insights and significantly enrich our analysis. Another natural extension of this paper would be to use the proposed *k*-SRNN approach to analyse and compare bond market turbulence in the United States in 2025 the announcement of the One Big Beautiful Bill Act, and in the United Kingdom in 2022

pandemic to counter-cyclical during those years when the Next Generation EU (NGEU) fiscal stimulus program was put in place.

following the announcement of the mini-budget. These topics are part of our future research agenda.

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Table 1. Principal Components Analysis.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
AUS	0.3164	-0.1367	-0.0430	-0.0648	-0.2305	0.1074	-0.1574	-0.4127	-0.3138	-0.4785	-0.3340	-0.4201
BEL	0.3219	-0.0551	0.0184	-0.0408	-0.2403	0.1304	-0.0421	-0.3800	0.6903	0.3823	-0.2151	0.0391
FIN	0.3179	-0.1240	-0.0925	-0.0493	-0.0489	0.1314	-0.0936	-0.0044	0.2706	-0.4962	0.6938	0.2082
FRA	0.3121	-0.1784	-0.0420	-0.0721	-0.1405	0.0746	-0.1425	-0.0635	-0.4597	0.6111	0.4423	-0.1839
GER	0.3092	-0.1957	-0.0726	-0.1653	0.0546	0.0862	-0.1414	0.7638	0.2083	-0.0034	-0.1971	-0.3708
GRE	0.0796	0.6471	-0.4658	-0.4073	-0.2880	-0.3045	-0.1114	0.0550	-0.0161	0.0045	0.0131	0.0244
IRE	0.2774	0.2797	0.8385	-0.1573	-0.1498	-0.2714	0.0758	0.0887	-0.0406	-0.0567	0.0471	0.0112
ITA	0.3043	0.1538	-0.1659	0.7222	-0.3522	-0.0851	0.4057	0.1831	-0.0631	-0.0174	-0.0274	0.0131
NET	0.3134	-0.1681	-0.0419	-0.0875	-0.0269	0.0857	-0.1888	0.1286	-0.2838	0.0026	-0.3485	0.7758
POR	0.2180	0.4973	0.0264	-0.0573	0.3812	0.6989	0.2383	-0.0290	-0.0872	0.0265	-0.0235	-0.0291
SPA	0.3048	0.1897	-0.0448	0.3693	0.5959	-0.3679	-0.4654	-0.1341	0.0514	0.0318	-0.0164	-0.0611
UK	0.2961	-0.2463	-0.1735	-0.3157	0.3653	-0.3693	0.6577	-0.1346	-0.0198	0.0028	-0.0309	-0.0033
EVR_k	0.7952	0.1766	0.0111	0.0085	0.0031	0.0025	0.0022	0.0003	0.0002	0.0001	0.0001	0.0000
CEV_k	0.7952	0.9719	0.9830	0.9915	0.9946	0.9971	0.9993	0.9996	0.9998	0.9999	1.0000	1.0000

Note: The explained variance ratio of each principal component k represents the proportion of total variance in the dataset accounted for by that component:

$$EVR_k = \lambda_k / \sum_{k=1}^{12} \lambda_k, k = 1, 2, \dots, 12.$$

The cumulative explained variance reflects the total proportion of variance retained by the first k principal components: $CEV_k = \sum_{j=1}^k \lambda_j / \sum_{j=1}^{12} \lambda_j, k = 1, 2, \dots, 12.$

Table 2. The k -RSNN algorithm.

Step 1: Rescale data. Let $\{x_t\}_{t=1}^T$ be a finite time series and two related time finite series: $\{y_t\}_{t=1}^T$ and $\{z_t\}_{t=1}^T$. Min-max normalisation each time series for data scaling to the range $[0, 1]$.

$$ts_t = \frac{ts_t - \min(ts_t)}{\max(ts_t) - \min(ts_t)}, \text{ where } ts = \{x, y, z\}.$$

Step 2. Create m -histories. The essence of m -histories lies in their capacity to captures the complexities of recurring patterns over time within the m -dimensional phase space of the ime series:

$$ts_t^m = (ts_t, ts_{t-1}, \dots, ts_{t-(m-1)}) \in \mathbb{R}^m, \quad t = m, m+1, \dots, T-1, \text{ where } ts = \{x, y, z\}.$$

Step 3. Calculate distances. Compute the distance metric between the last vector $x_T^m \in \mathbb{R}^m$ and all vectors in the training dataset $(y_t^m, z_t^m) \in \mathbb{R}^m \times \mathbb{R}^m$:

$$d_t(y_t^m, x_T^m) + d_t(z_t^m, x_T^m) \quad t = m, m+1, \dots, T-1$$

Step 4. Identify k related simultaneous nearest neighbours in both time series. Order all simultaneous vectors in the training dataset from nearest to farthest from the last vector $x_T^m \in \mathbb{R}^m$, and select the simultaneous closest k vectors in both related series:

$$y_{t_1}^m, y_{t_2}^m, \dots, y_{t_k}^m \text{ and } z_{t_1}^m, z_{t_2}^m, \dots, z_{t_k}^m$$

Step 5. Aggregate neighbour targets. The prediction $\hat{x}_{T+1}$ is obtained as an appropriate average or median of the target values corresponding to the observations following the k -associated simultaneous m -histories in both related series.

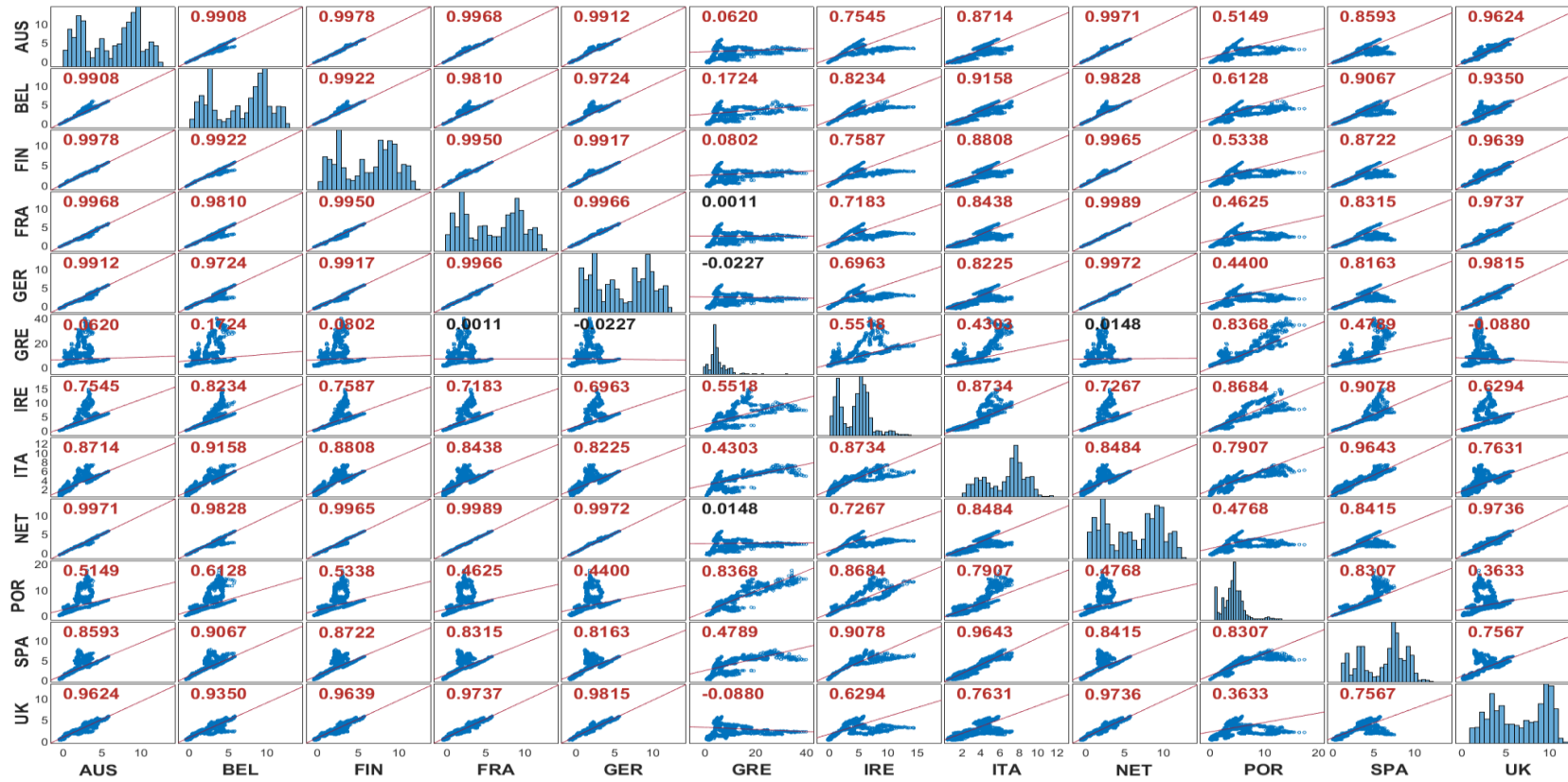
Note: The table details the sequential steps involved in the k -RSNN algorithm.

Table 3. Runtime of the alternative prediction algorithms.

Algorithms	<i>k</i> -NN		<i>k</i> -RSNN	ARIMA-GARCH		LSTM
Individual or Groups	UK	EA core countries	Italy and Spain	Greece, Ireland and Portugal	UK	UK
Forecast period						
October 17-31, 2022	0.3802	0.5855	0.4538	0.4627	3.3824	148.5959
November 1, 2022-January 13, 2023	3.6483	5.2753	4.0524	4.3342	4.2111	184.9236
January 16-June 30, 2023	79.2901	83.9737	76.8497	80.9894	5.0760	223.2586

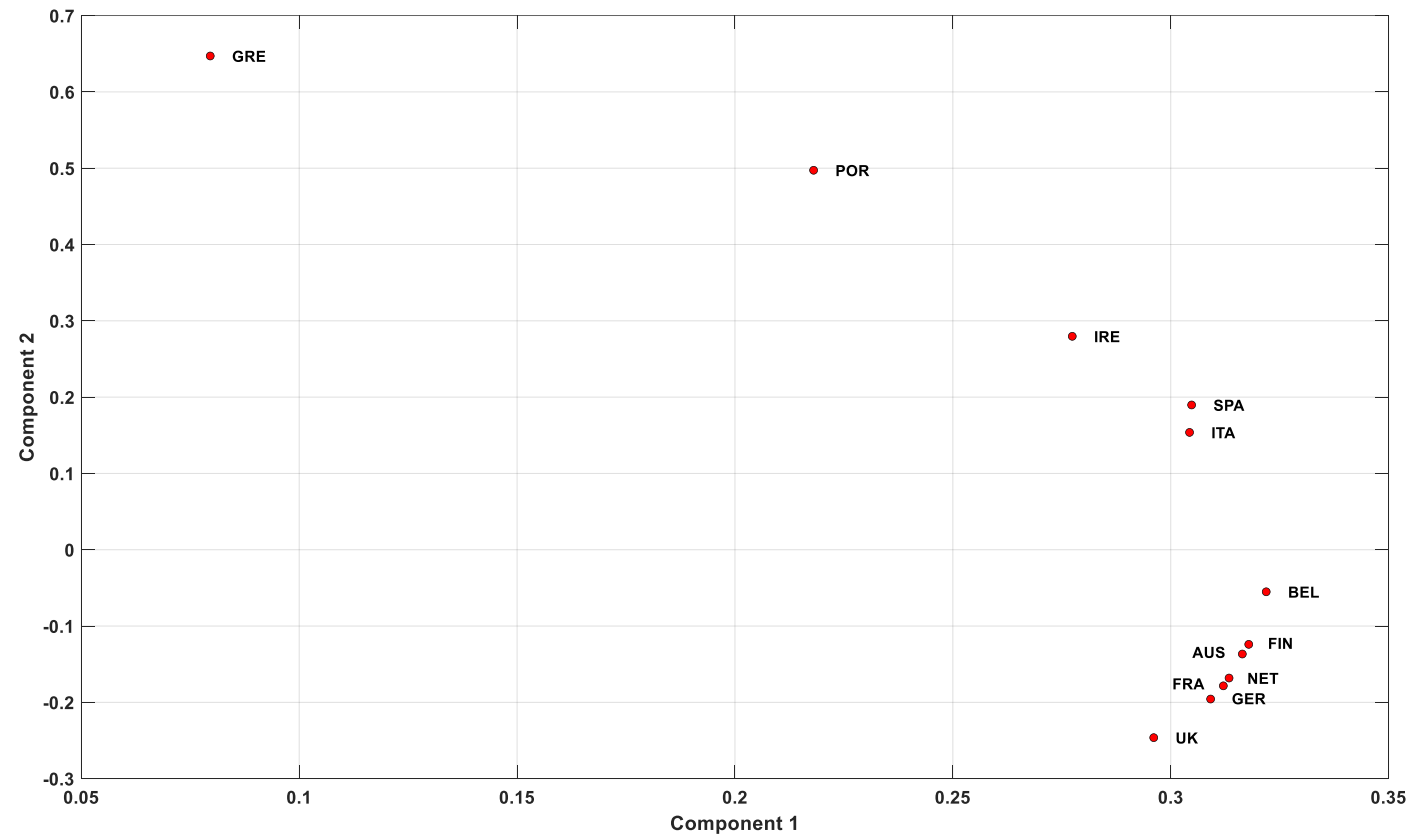
Note: In this table, we evaluate the effectiveness of the candidate algorithms to forecast (i.e. with faster runtimes). We measure the execution time required by each algorithm on an 11th Gen Intel(R) Core (TM) i7-1165G7 2.80GHz processor machine with 32 Gbytes of RAM. The runtime is measured in seconds. For LSTM models, the runtime indicates the total times computed over 100 independently trained models.

Figure 1. Correlation matrix plot.



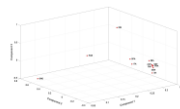
Note: The red font indicate significance at 5 % level in the correlation matrix plot

Figure 2. Principal Components Analysis (2D).



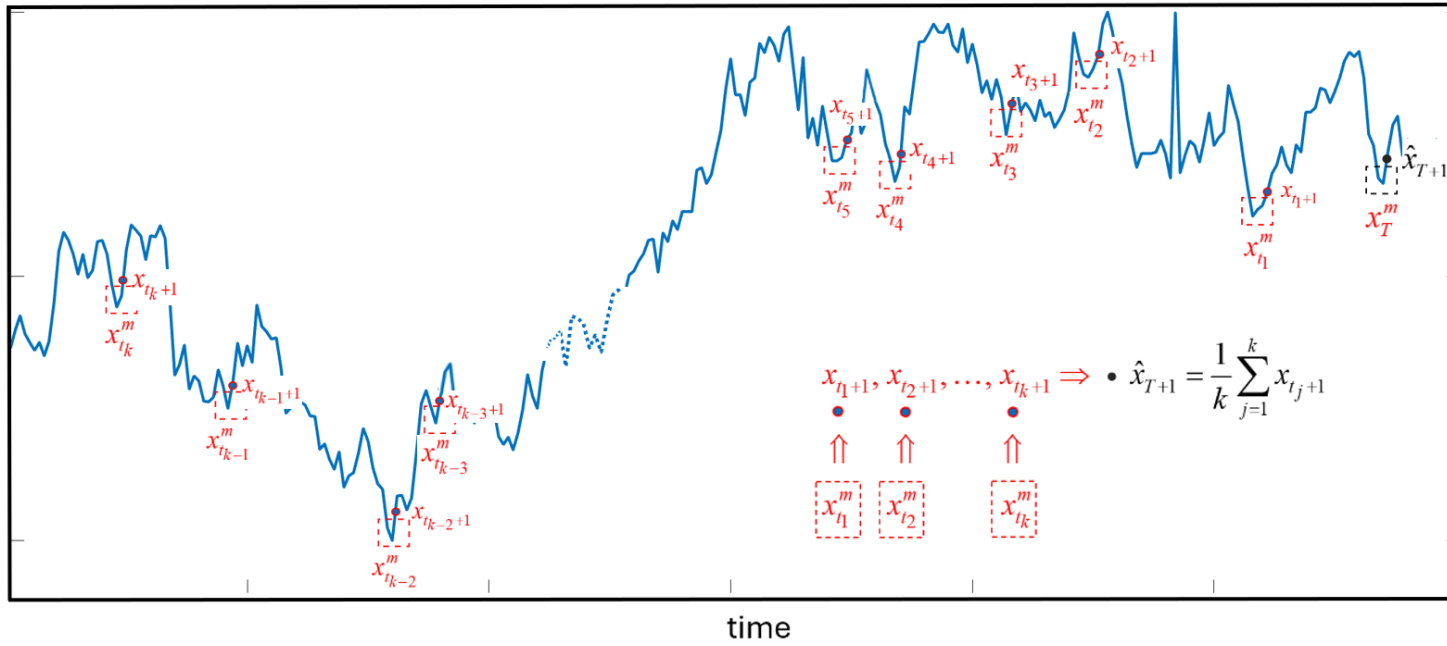
Note: The geometric coordinates assigned to each country are based on the two selected principal components. The plot reveals a clustering pattern, suggesting the existence of two underlying groups within the euro area: one comprising central countries (Austria, Belgium, Finland, France, Germany, and the Netherlands, along with the UK), and another consisting of peripheral countries (Greece, Ireland, Italy, Portugal, and Spain).

Figure 3. Principal Components Analysis (3D).



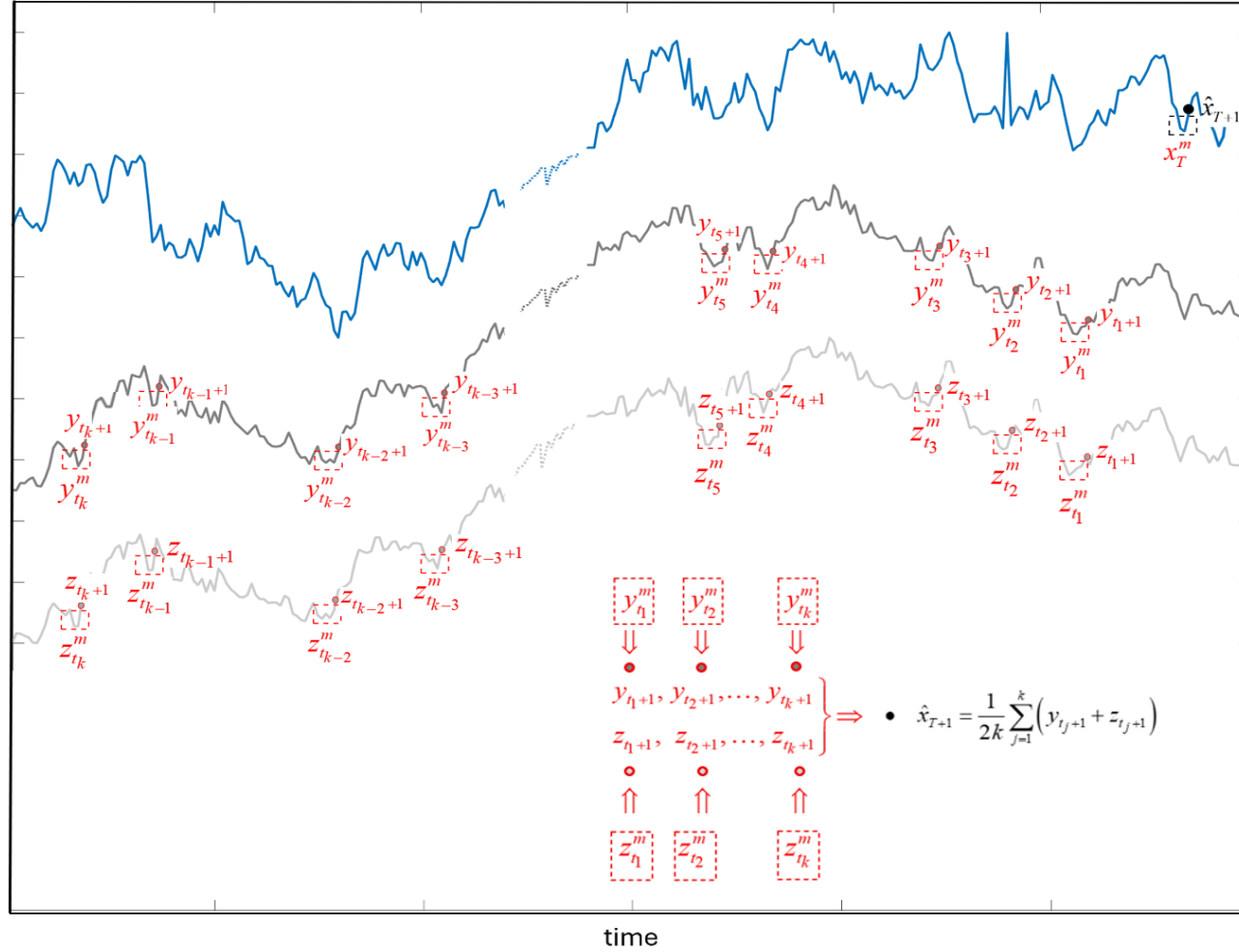
Note: The geometric coordinates assigned to each country are derived from the three selected principal components. The resulting distribution reveals distinct clustering patterns, indicating the presence of three underlying groups within the euro area: a central group (Austria, Belgium, Finland, France, Germany, and the Netherlands), an outer peripheral group (Greece, Ireland, and Portugal), and an inner peripheral group (Spain and Italy), which appears clearly differentiated from the outer periphery.

Figure 4. The k -NN analysis.



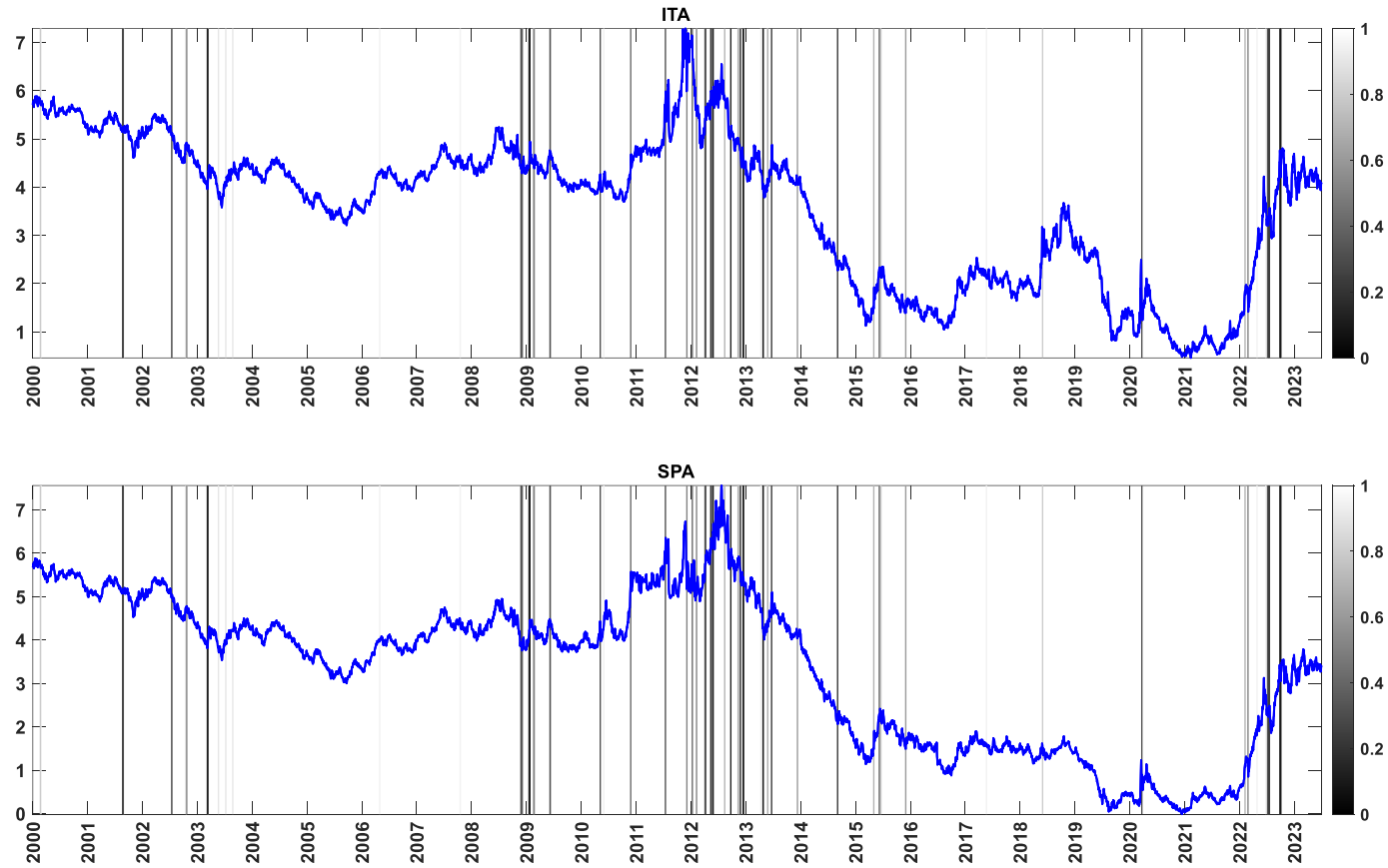
Note: The figure provides a representative schematic depiction of the k -NN analysis methodology.

Figure 5. The k -RSNN analysis.



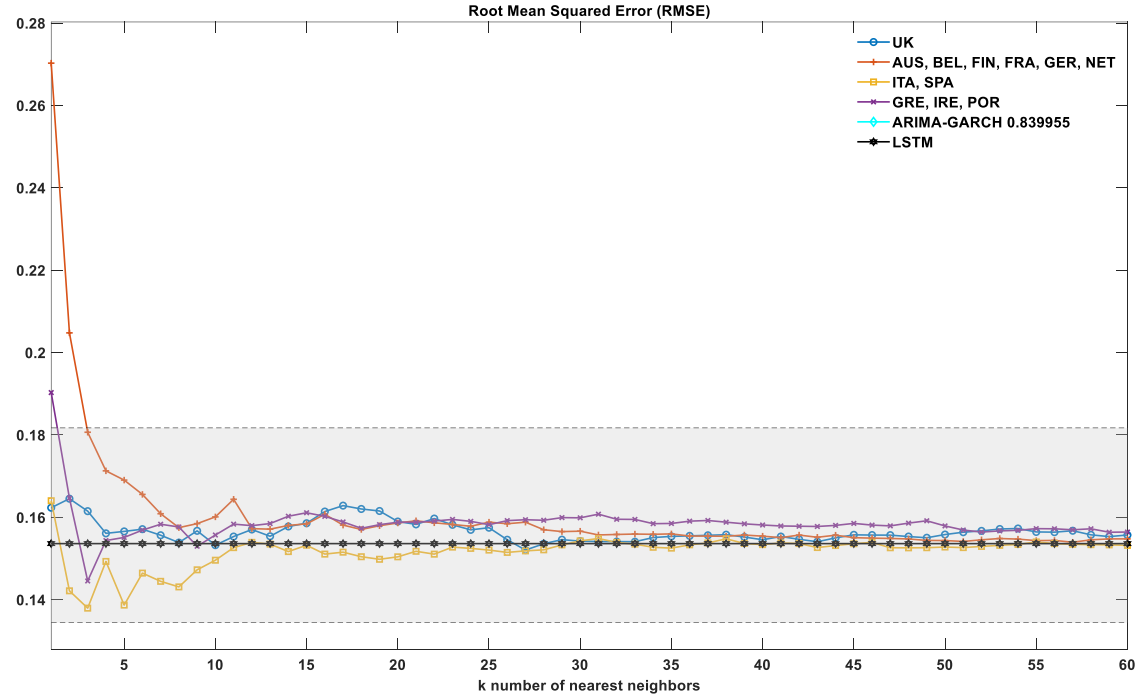
Note: The figure provides a representative schematic depiction of the k -RSNN analysis methodology.

Figure 6. Analogies with the behaviour of the UK government bond yield during 17 October - 31 October 2022 (11 days) detected by the 10-RSNN analysis in the government bond yield series of Italy and Spain.



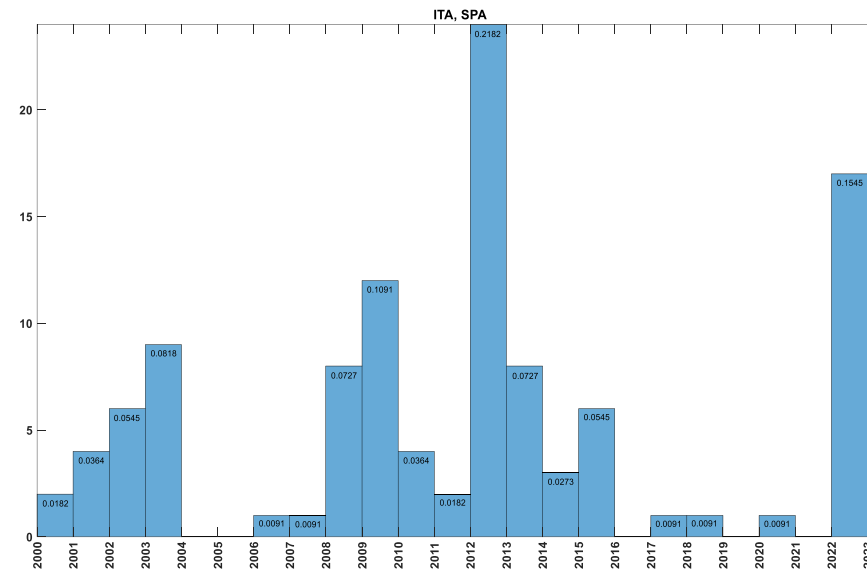
Note: The colour map linearly maps the values of the proximity of analogies to an interval [0, 1]. A value of 0 (black) indicates the most similarity, and 1 (white) indicates the most dissimilarity.

Figure 7. Root mean square error of forecasts based on detected analogies for the forecast period: October 17 to 31, 2022.



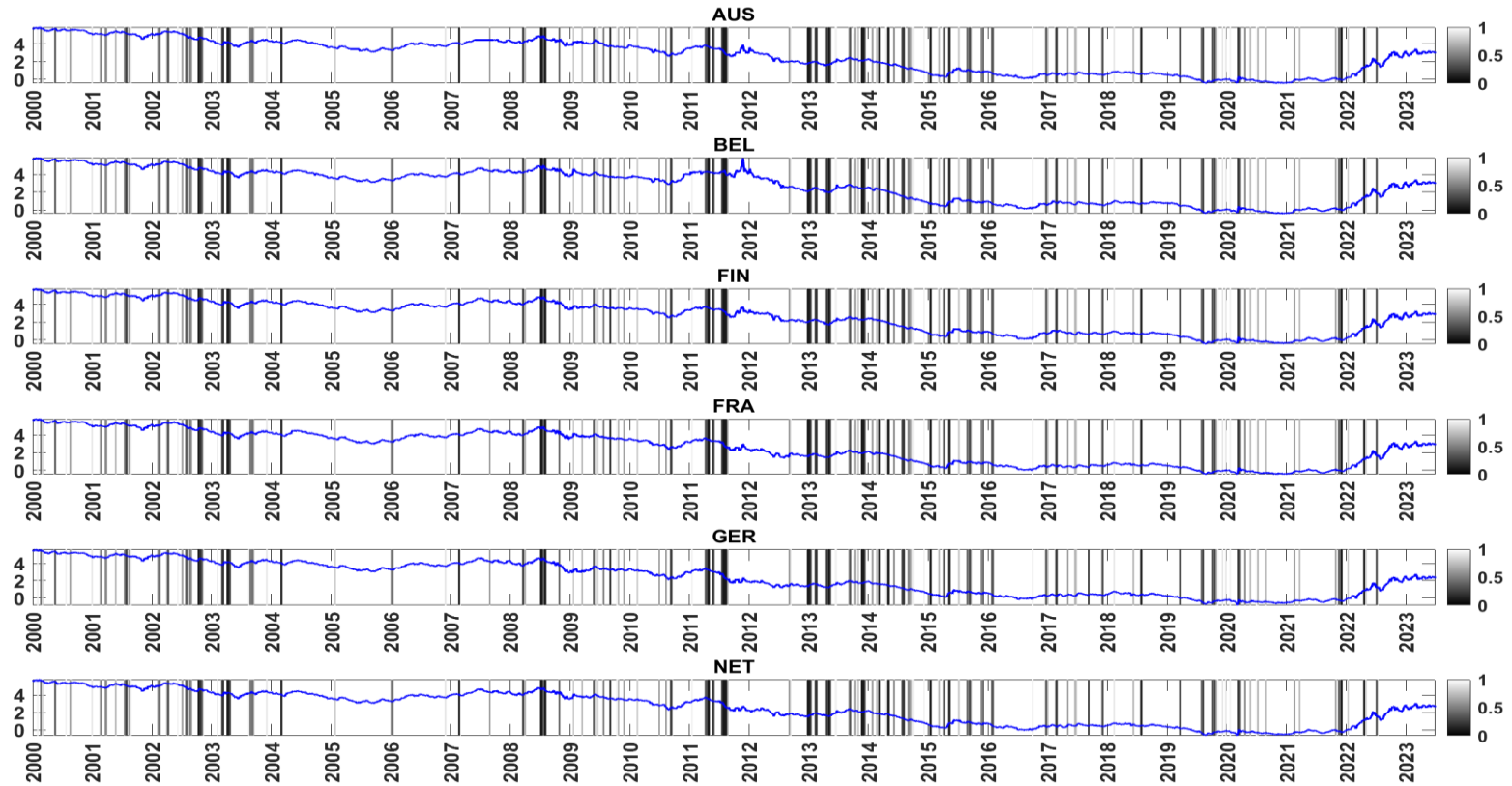
Note: Root Mean Square Error (RMSE) of forecasts generated by the univariate k -NN and multivariate k -RSNN models (computed for each group of analogies) across different values of k , as well as the ARIMA-GARCH model (whose RMSE lies outside the figure and is indicated in the legend), and multiple vanilla LSTM models applied to the UK government bond yield time series. For the LSTM models, the black line represents the average forecast, while the grey shaded area denotes empirical uncertainty bands corresponding to the 5th and 95th percentiles, calculated from 100 independently trained models.

Figure 8. Histogram of the analogies with the behaviour of the UK government bond yield during 17 October - 31 October 2022 (11 days) detected by the *10*-RSNN analysis in the government bond yield series of Italy and Spain.



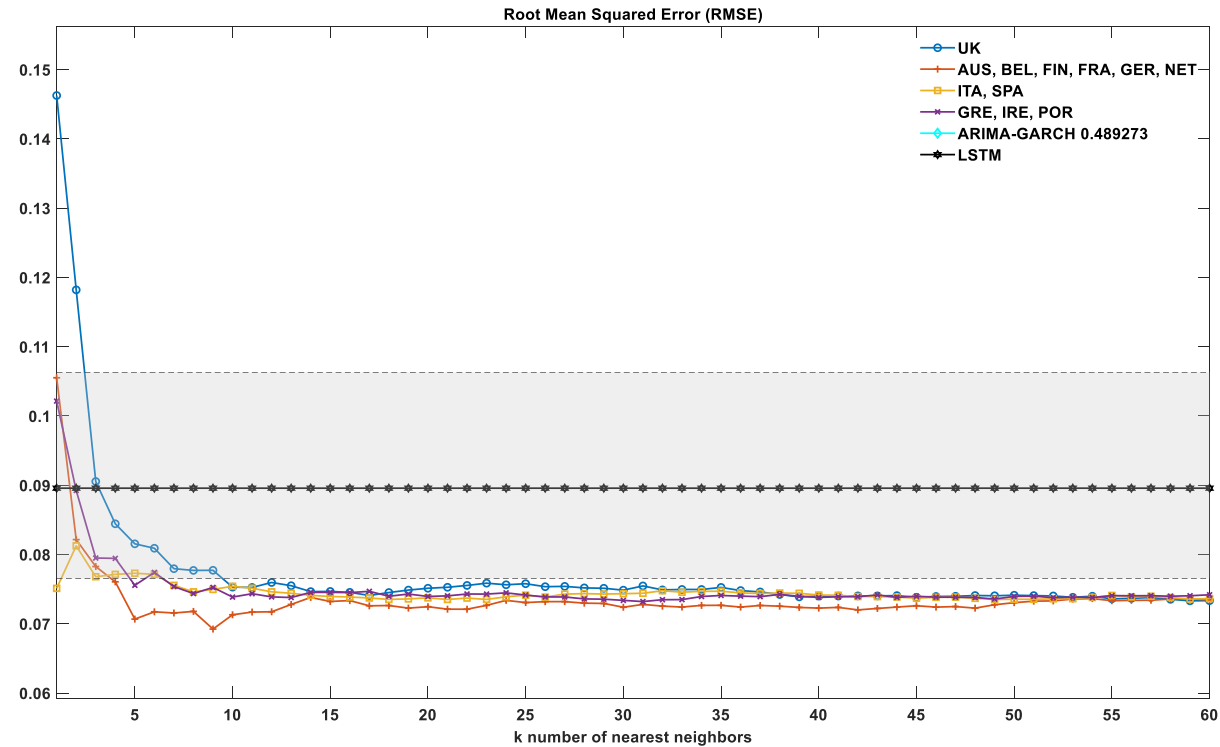
Note: The histogram illustrates the annual frequency distribution of episodes identified in the historical behaviour of Italy and Spain, as detected by the *10*-RSNN predictors. Most episodes are concentrated during the euro area sovereign debt crisis period (2009–2012).

Figure 9. Analogies with the behaviour of the UK government bond yield during 1 November 2022- 13 January 2023 (54 days) detected by the 10-RSNN analysis in the government bond yield series of the EA core countries.



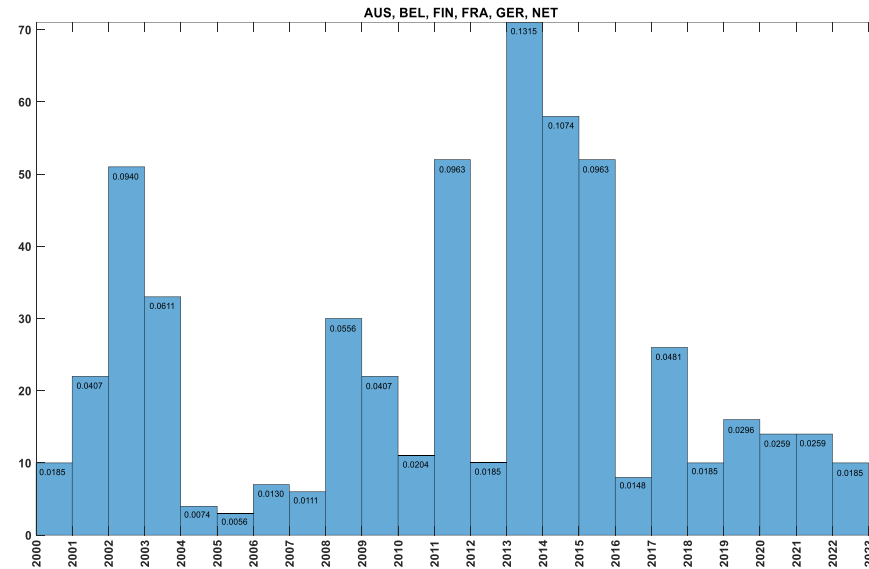
Note: The colour map linearly maps the values of the proximity of analogies to an interval $[0, 1]$. A value of 0 (black) indicates the most similarity, and 1 (white) indicates the most dissimilarity.

Figure 10. Root mean square error of forecasts based on detected analogies for the forecast period: November 1, 2022, to January 13, 2023.



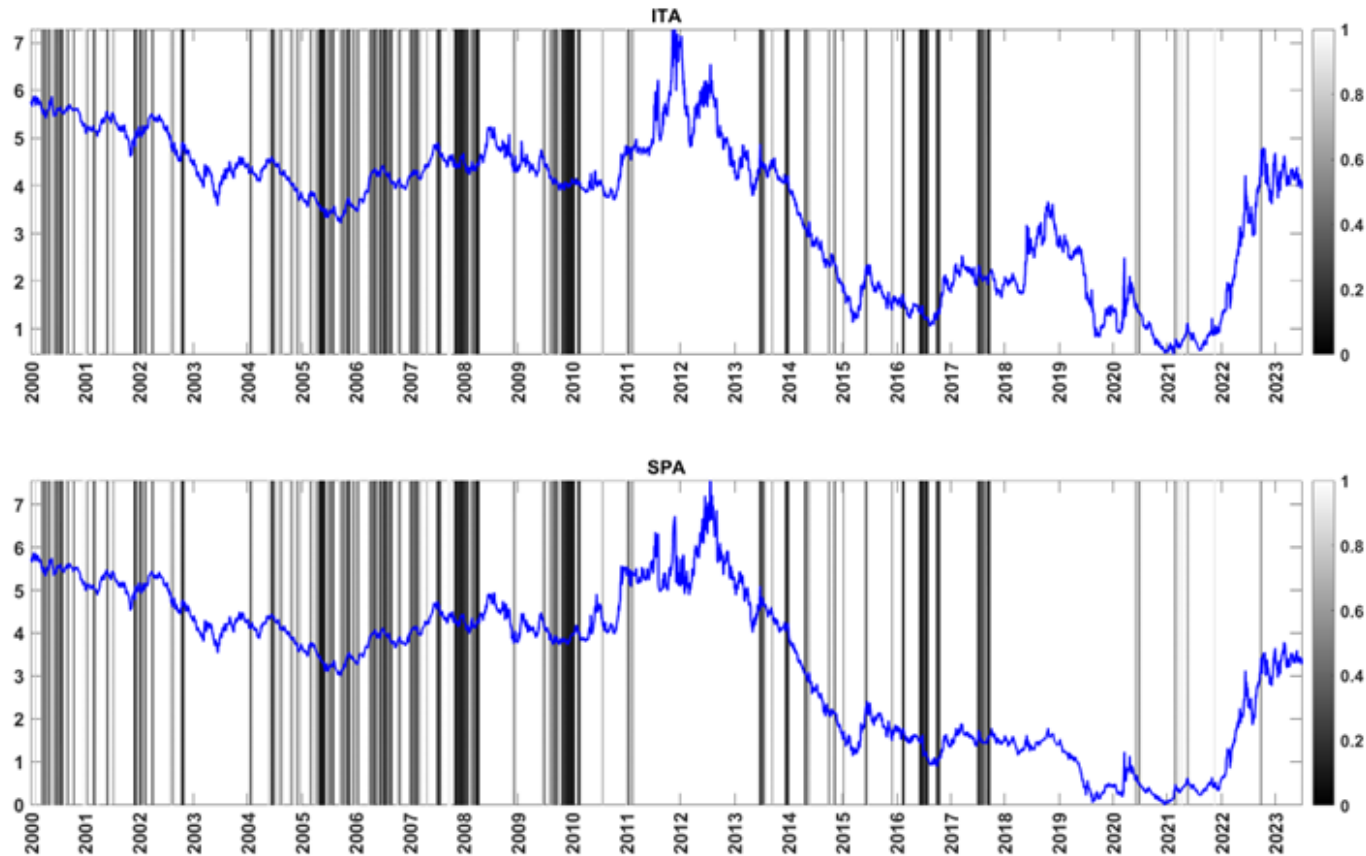
Note: Root Mean Square Error (RMSE) of forecasts generated by univariate k -NN and multivariate k -RSNN models (computed for each group of analogies) across different values of k , as well as by the ARIMA-GARCH model (whose RMSE lies outside the figure and is indicated in the legend), and by multiple vanilla LSTM models, all applied to the UK government bond yield time series. For the LSTM models, the black line represents the average forecast, while the grey shaded area denotes empirical uncertainty bands corresponding to the 5th and 95th percentiles, computed from 100 independently trained models.

Figure 11. Histogram of the analogies with the behaviour of the UK government bond yield during 1 November 2022- 13 January 2023 (54 days) detected by the 10-RSNN analysis in the government bond yield series of the EA core countries.



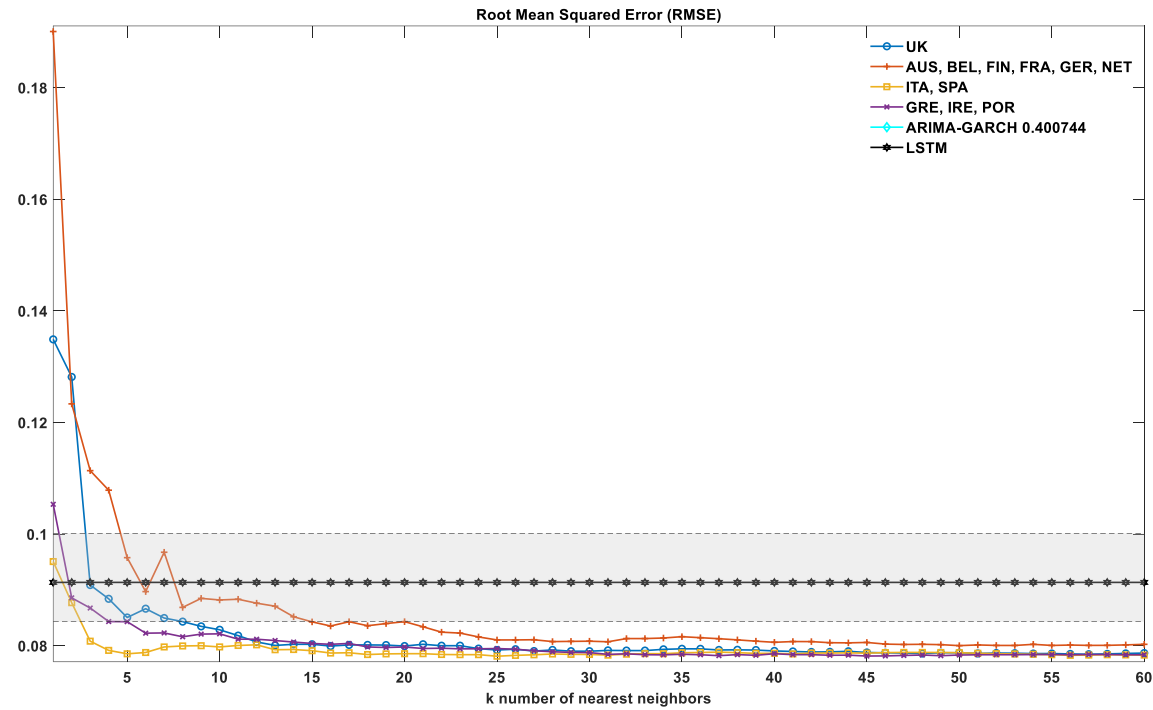
Note: The histogram illustrates the annual frequency distribution of episodes identified in the historical behaviour of core euro area countries (Austria, Belgium, Finland, France, Germany, and the Netherlands), as detected by the 10-RSNN predictors. Most episodes are concentrated in the 2013–2015 period.

Figure 12. Analogies with the behaviour of the UK government bond yield series during 16 January 2023 - 30 June 2023 (120 days) detected by the 10-RSNN analysis in the government bond yield series of Italy and Spain.



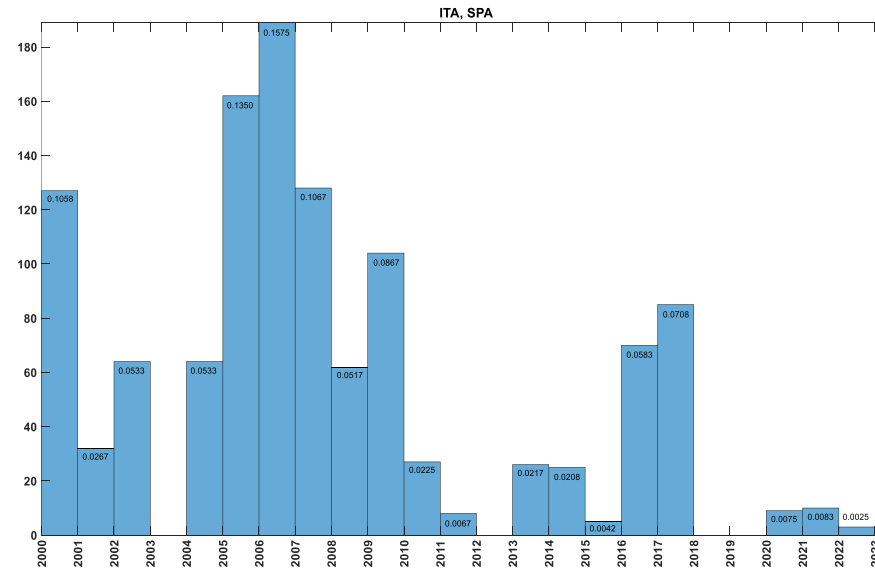
Note: The colour map linearly maps the values of the proximity of analogies to an interval $[0, 1]$. A value of 0 (black) indicates the most similarity, and 1 (white) indicates the most dissimilarity.

Figure 13. Root mean square error of forecasts based on detected analogies for the forecast period: January 16, 2023, to June 30, 2023.



Note: Root Mean Square Error (RMSE) of forecasts generated by univariate k -NN and multivariate k -RSNN models (computed for each group of analogies) across different values of k , as well as by the ARIMA-GARCH model (whose RMSE lies outside the figure and is indicated in the legend), and by multiple vanilla LSTM models applied to the UK government bond yield time series. For the LSTM models, the black line represents the average forecast, while the grey shaded area denotes empirical uncertainty bands corresponding to the 5th and 95th percentiles, calculated from 100 independently trained models.

Figure 14. Histogram of the analogies with the behaviour of the UK government bond yield series during 16 January 2023 - 30 June 2023 (120 days) detected by the 10-RSNN analysis in the government bond yield series of Italy and Spain.



Note: The histogram illustrates the annual frequency distribution of episodes identified in the historical behaviour of Italy and Spain, as detected by the 10-RSNN predictors. Most episodes are concentrated in the years preceding the onset of the euro area sovereign debt crisis (2005–2009).

Appendix 1. The ARIMA-GARCH model

The ARIMA (p, d, q) can be expressed as:

$$\phi_p(L)(1-L)^d(x_t - \mu) = \mathcal{G}_q(L)e_t$$

or

$$\left(1 - \sum_{i=1}^p \phi_i L^i\right)(1-L)^d(x_t - \mu) = \left(1 - \sum_{j=1}^q \mathcal{G}_j L^j\right)e_t$$

where:

$$\phi_p(L) = 1 - \sum_{i=1}^p \phi_i L^i \text{ and } \mathcal{G}_q(L) = 1 - \sum_{j=1}^q \mathcal{G}_j L^j$$

are polynomials in terms of L of degree p and q .

y_t is the time series, e_t is the random error at time period t , μ is the mean of the model, d is the order of the difference operator. $\phi_1, \phi_2, \dots, \phi_p$ and $\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_q$ are the parameters of autoregressive and moving average terms with order p and q respectively. Finally, L is the difference operator defined as $(1-L)x_t = x_t - x_{t-1}$.

We utilise the Akaike Information Criterion (AIC) to determine the optimal order (p, d, q) of the ARIMA model.

The general GARCH (r, s) model for conditional heteroskedasticity, as proposed by Bollerslev (1986), is expressed as follows:

$$x_t = \mu_t + z_t$$

where:

μ_t is conditional mean of x_t ,

z_t is the shock at time t ,

$$z_t = \sigma_t e_t$$

where:

$$e_t \rightarrow iid N(0,1)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^r \alpha_i z_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2$$

where:

σ_t^2 is the conditional variance of y_t ,

α_0 is a constant term,

r is the order of the ARCH terms,

s is the order of the GARCH terms,

α_i and β_j are the coefficients of the ARCH and GARCH parameters, respectively,

with constraints:

$$\alpha_0 > 0$$

$$\alpha_i \geq 0, \text{ for } i = 1, 2, \dots, r$$

$$\beta_j \geq 0, \text{ for } j = 1, 2, \dots, s$$

$$\sum_{i=1}^r \alpha_i + \sum_{j=1}^s \beta_j < 1$$

In our analysis, we use the residuals from the ARIMA model as input for the GARCH model to capture the time-varying volatility commonly observed in financial time series.

Examining the partial autocorrelation function (PACF) of the squared residuals can determine the order (r, s) of the GARCH model.

Finally, we obtain a comprehensive forecast by combining the forecasts from the ARIMA model, which captures the conditional mean, with those from the GARCH model, which models the conditional variance.

The estimation procedure for the ARIMA and GARCH models is based on the maximum likelihood method.

Appendix 2. LSTM network structure

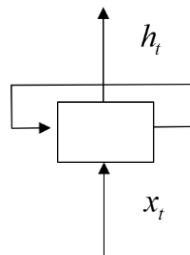
Artificial neural network (ANNs) is inspired by the human nervous system and can be defined as computational models which use linked layers of artificial neurons to emulate the biological functions of information processing, information storage and learning.

In an ANN, the biological neuron and its connections are simplified into a mathematical model called a perceptron, which was first introduced by McCulloch and Pitts in 1943. The multilayer perceptron (MLP) approach of supervised learning is the most commonly recognised type of ANN, consisting of a single input and output layer together with one or more hidden layers. An MLP is a class of feedforward ANN. **Within the machine learning community**, it is well known that a sufficiently large multi-layer feedforward neural network (FFNN) can accurately approximate any function, without requiring any initial or extra information about data, such as the distribution (Hornik *et al.*, 1989).

ANN models run by constructing a nonlinear relationship between dependent and independent variables, depending on a set of experimental data. The artificial neurons are linked by means of weighted connections. In ANN models, procedures such as data collection and analysis, network structure design, managing hidden layers, network simulation, weight assignment and bias trade-off are processed via learning and training methods.

Recurrent neural networks (RNNs) (Rumelhart *et al.*, 1986) derived from FFNNs are another type of ANN, characterised by the presence of recurrent connections between multiple layers, where each layer is composed of one or more neurons that connect to the previous layer as well as to the next layer in the sequence. A typical RNN unit is shown in Figure A2.1. Unlike FFNNs, RNNs handle temporal information and are used for processing time series or data sequences.

Figure A2.1. RNN unit has loops.



A single RNN has only one internal memory, h_t , which is computed as

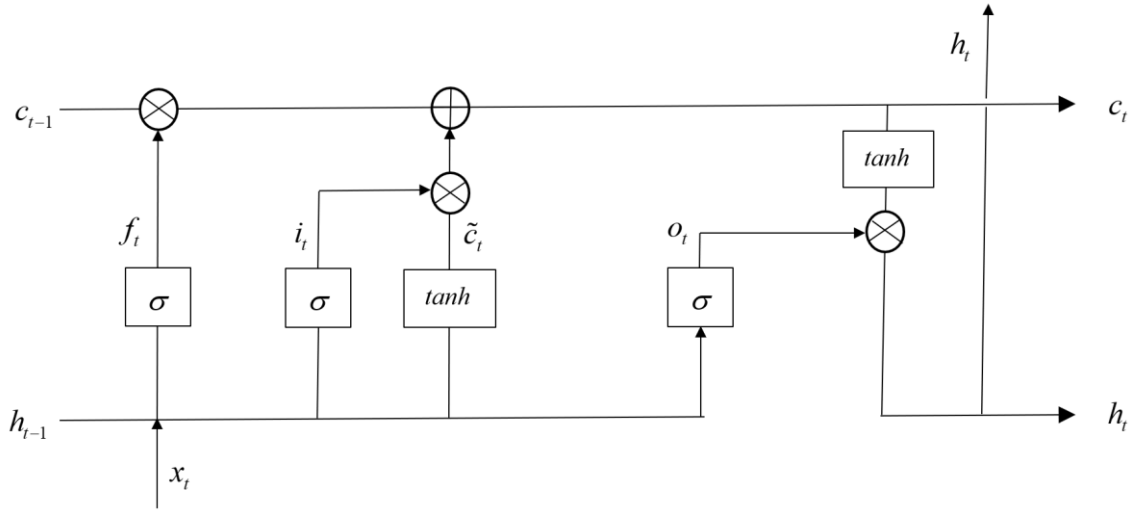
$$h_t = \varphi(W_y y_t + W_h h_{t-1} + b)$$

where φ denotes a nonlinear activation function. Although basic RNNs are capable of dealing with time series forecasting, their vulnerability to vanishing and/or exploding gradients limits

their application to that of learning short-term relations within the observations (Bengio *et al.*, 1994).

Among the different RNN architectures, LSTM is a special type that was devised to overcome the above limitation. The most frequently used LSTM architecture is the Vanilla LSTM, which has been shown to perform reasonably well on various data sets (Greff *et al.*, 2017). A Vanilla LSTM model has a single hidden layer of LSTM units and an output layer that is used for prediction. A Vanilla LSTM unit structure is illustrated in Figure A2.2, but other variants have also been suggested (see Greff *et al.* (2017) for a review). This cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. The role of the input gate is to determine what new information can be entered into the memory cell to update the state of the cell. The forget gate is used to decide what information in the memory cell should be delivered and what information can be retained to update the state of the cell units along with the new input information. The output gate is employed to filter out information from the memory cell and to output the information needed to predict future values.

Figure A2.2. Vanilla LSTM unit has gates.



At time t , x_t is the input data of the LSTM unit (e.g., the return), h_{t-1} is the output of the LSTM unit at the previous moment, c_t is the value of the memory cell and h_t is the output of the LSTM unit. For the version used in this paper, the computation process inside the LSTM units can be expressed mathematically as:

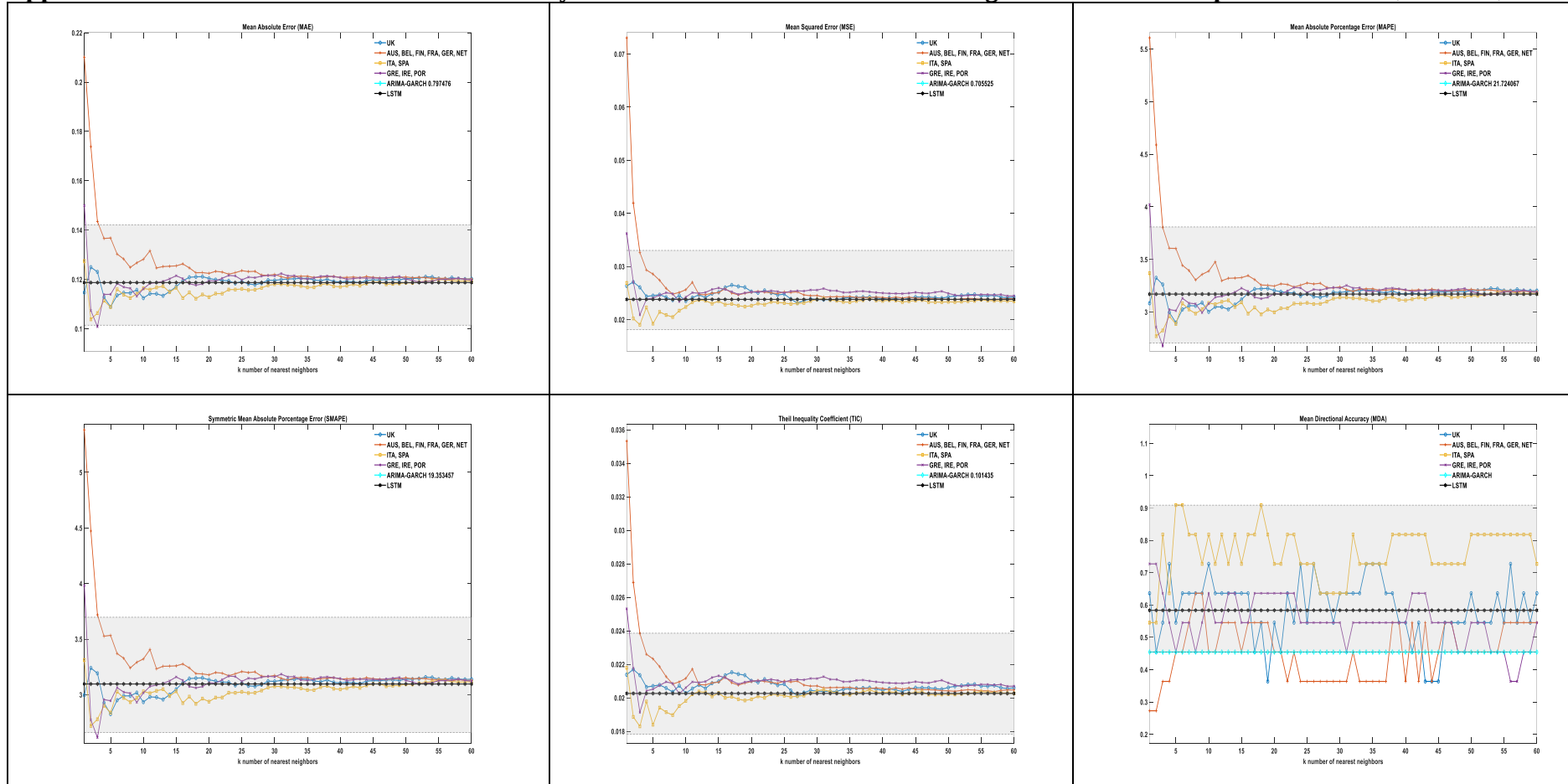
$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{c}_t &= \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \end{aligned}$$

$$\begin{aligned}
c_t &= f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
h_t &= o_t \otimes \tanh(c_t)
\end{aligned}$$

where σ denotes the logistic sigmoid function and $\otimes$ represents element-wise multiplication.

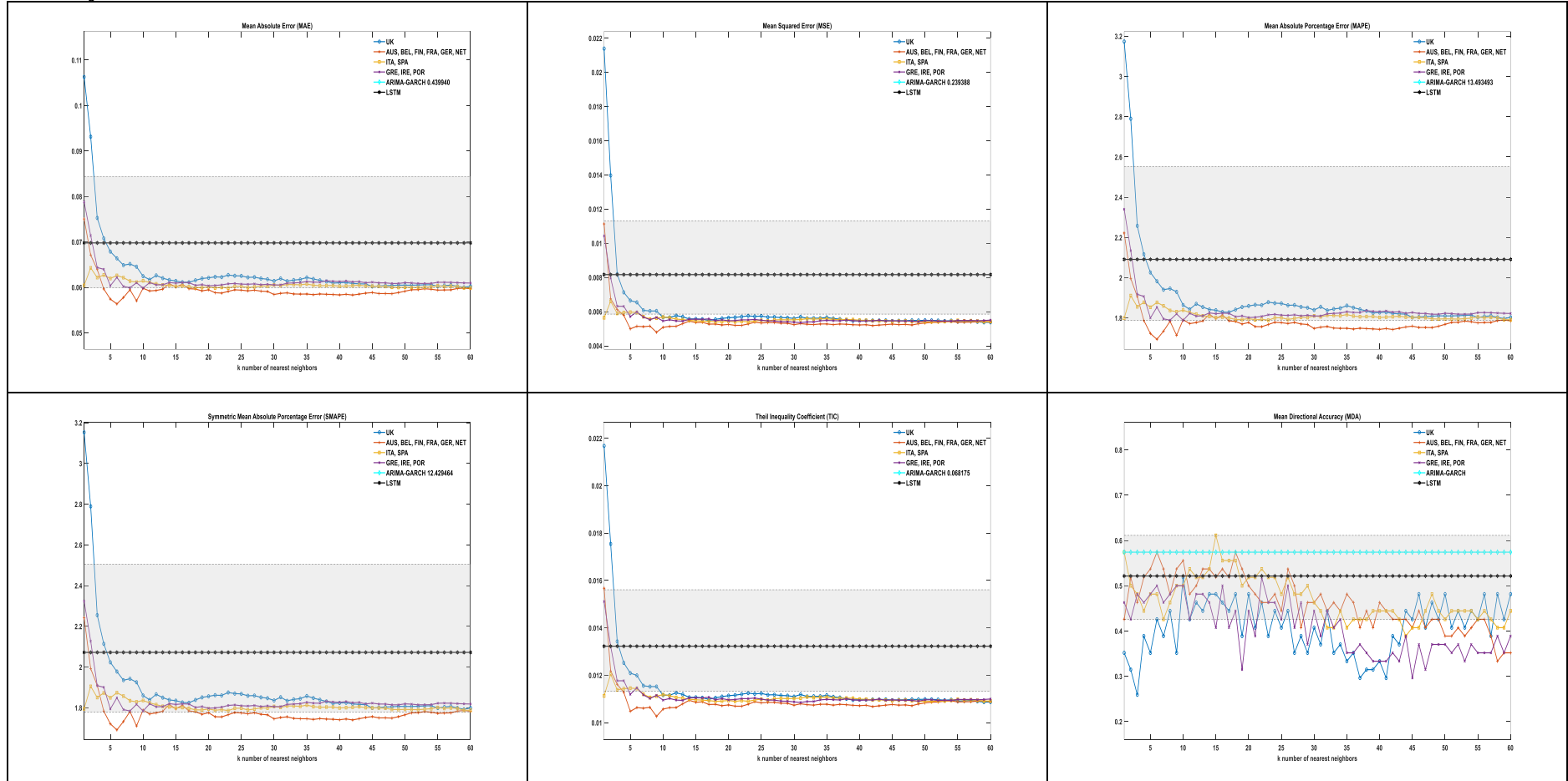
In LSTM networks, as the numbers of layers and of neurons in each layer increase, the number of parameters in the model rises extremely fast which can easily result in over-fitting, especially when data are scarce. To overcome this problem, Hinton et al. (2012) proposed the application of a dropout process, by which, during every network training episode, some units are randomly discarded from the network at a stage p . Although the parameters of these discarded neurons are not updated during training, all of the neurons are considered in the testing process (Srivastava et al., 2014).

Appendix 3. Alternative measures of the accuracy of forecasts based on detected analogies for the forecast period: October, 17 to 31, 2022.



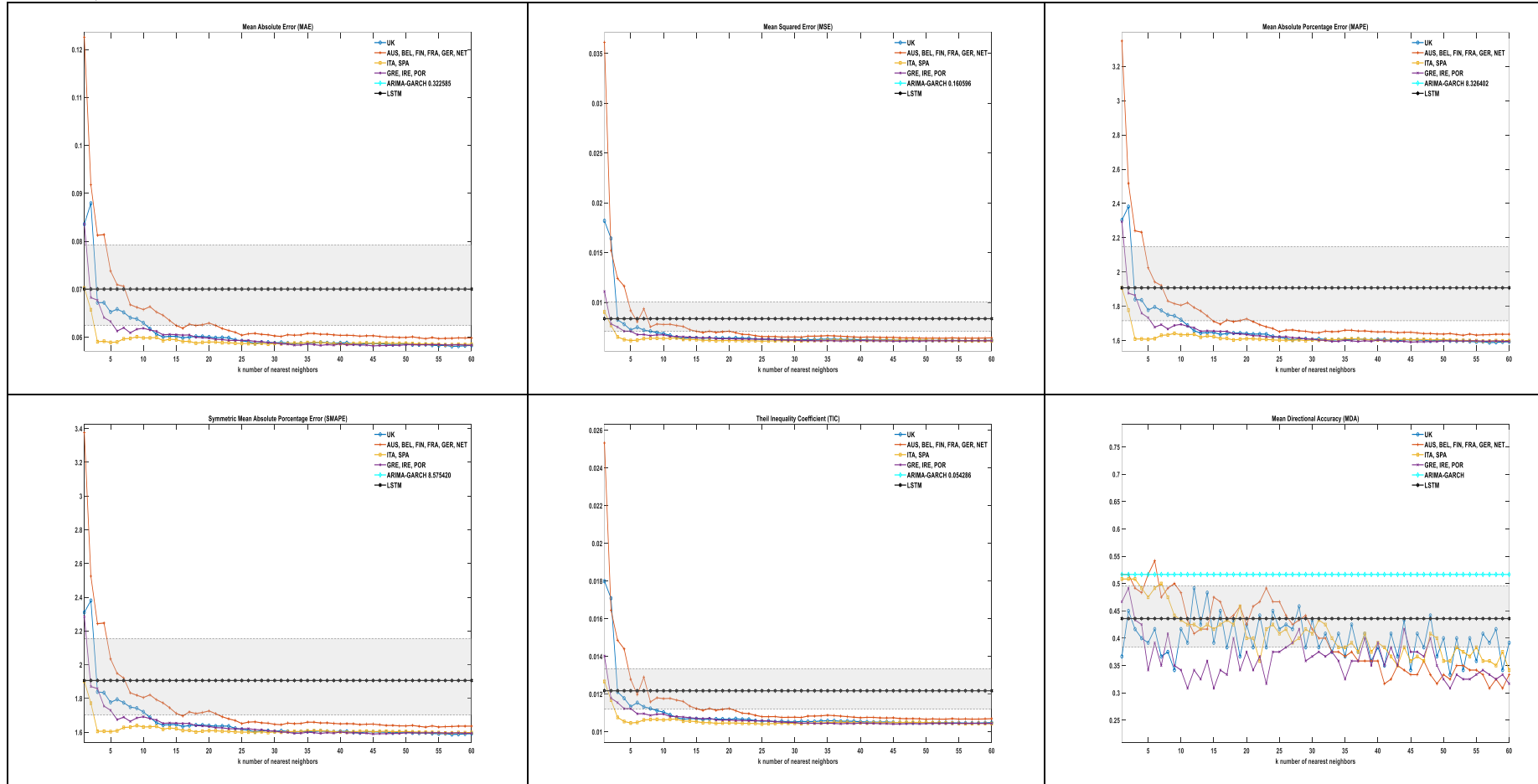
Note: Additional accuracy metrics for forecasts generated by univariate k -NN and multivariate k -RSNN models (computed for each group of analogies) across various values of k , as well as the ARIMA-GARCH model (whose value, if outside the figure, is indicated in the legend) and multiple vanilla LSTM models applied to the UK government bond yield time series. For the LSTM models, the black line represents the average forecast, while the gray shaded area denotes empirical uncertainty bands at the 5th and 95th percentiles, calculated from 100 independently trained models.

Appendix 4. Alternative measures the accuracy of forecasts based on detected analogies for the forecast period: November 1, 2022, to January 13, 2023.



Note: Additional accuracy metrics of forecasts generated by univariate k -NN and multivariate k -RSNN models (computed for each group of analogies) across different values of k , as well as the ARIMA-GARCH model (whose value, if outside the figure, is indicated in the legend) and multiple vanilla LSTM models applied to the UK government bond yield time series. For the LSTM models, the black line represents the average forecast, while the gray shaded area denotes empirical uncertainty bands at the 5th and 95th percentiles, calculated over 100 independently trained models.

Appendix 5. Alternative measures of the accuracy of forecasts based on detected analogies for the forecast period: January 16, 2023, to June 30, 2023.



Note: Additional accuracy metrics of forecasts generated by univariate k -NN and multivariate k -RSNN models (computed for each group of analogies) across different values of k , as well as the ARIMA-GARCH model (whose value, if outside the figure, is indicated in the legend) and multiple vanilla LSTM models applied to the UK government bond yield time series. For the LSTM models, the black line represents the average forecast, while the gray shaded area denotes empirical uncertainty bands at the 5th and 95th percentiles, calculated over 100 independently trained models.