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GLOBAL PATTERNS AND EXTREME EVENTS IN SOVEREIGN RISK PREMIA: A FUZZY VS DEEP LEARNING COMPARATIVE

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Abstract. Investment in foreign countries has become more common nowadays and this implies that there may be risks inherent to these investments, being the sovereign risk premium the measure of such risk. Many studies have examined the behaviour of the sovereign risk premium, nevertheless, there are limitations to the current models and the literature calls for further investigation of the issue as behavioural factors are necessary to analyse the investor's risk perception. In addition, the methodology widely used in previous research is the regression model, and the literature shows it as scarce yet. This study provides a model for a new of the drivers of the government risk premia in developing countries and developed countries, comparing Fuzzy methods such as Fuzzy Decision Trees, Fuzzy Rough Nearest Neighbour, Neuro-Fuzzy Approach, with Deep Learning procedures such as Deep Recurrent Convolution Neural Network, Deep Neural Decision Trees, Deep Learning Linear Support Vector Machines. Our models have a large effect on the suitability of macroeconomic policy in the face of foreign investment risks by delivering instruments that contribute to bringing about financial stability at the global level.

Keywords: sovereign risk premium, fuzzy decision trees, neuro-fuzzy approach, deep neural decision trees, deep recurrent convolutional neural networks.

JEL Classification: C63, E43, G1.

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1. Introduction

Sovereign risk premia are the yield that buyers require of a country to acquire its public debt compared to the yield required of the reference country considered to be a risk-free asset. It is a measurement of the "cost premium" that one country has to pay over another for financing in the markets (Özmen, 2019). For the calculation of the risk premium, sovereign spreads are considered, and these are determined as the spreads between sovereign debt returns and the returns regarded as a without-risk state bond of similar duration. It is therefore an indemnity to lenders for the risks of maintaining a high-risk investment asset up to its expiration. The greater the risk, the greater the funding charge and conversely (Fontana & Langedijk, 2019; Corradin & Schwaab, 2023). Thus, sovereign premiums are related to the country's likelihood of being in default on its liabilities. This, of course, implies that as a country's political and economic circumstances vary, so too does its risk premia (Palić et al., 2017; Andrade et al., 2023).

The last financial crisis generated significant levels of macroeconomic disequilibrium, including weak economic development, high levels of unemployment, fiscal and current account deficits, and a fast spread of public borrowing (Malliaropulos & Migiakis, 2018; Badarau et al., 2014; Baldacci & Manmohan, 2010). This led, in general, to a decline in the access conditions to financial markets and, in particular, to a considerable rise in government bond risk. As a result, the discussion on the drivers of the government risk premia is now the focus of attention (Balima et al., 2017).

In recent literature, some models have been developed that analyse the determinants of the sovereign risk premium (Andrade et al., 2023; Cecchetti, 2020; Mpapalida & Malikane, 2019; Özmen, 2019; Augustin et al., 2018; Palić et al., 2017). These studies show that the creditor threat shock of an economy is not restricted to its impact on government bonds, rather it also reflects in the borrowing charges in the economy's manufacturing section. Di Cesare et al. (2012) concluded that the increase in sovereign differentials in the eurozone can not be completely clarified by such macroeconomic drivers as debt-to-GDP ratios, public budgetary shortfall and GDP enlargement, but also by financial and global determinants. For this reason, the literature demands novel approaches to models that assist decision-makers to take into account behavioural drivers, as well as to build or pilot test new indicators related to sentiment and market expectative, since investors' awareness of risk is very affected by several behavioural aspects (Aristei & Martelli, 2014).

To cover this need shown by the literature, the present study tries to model the sovereign risk premium at a global level, to accurately capture its behaviour. This model is built from a 34-country sample, covering both developing and advanced countries, comparing Fuzzy methods such as Fuzzy Decision Trees, Fuzzy Rough Nearest Neighbour, Neuro-Fuzzy Approach, with Deep Learning procedures such as Deep Neural Decision Trees, Deep Recurrent Convolution Neural Networks, Deep Learning Linear Support Vector Machines, achieving levels of precision of more than 84.05%, that implies excellent precision results. The model that has achieved the highest levels of accuracy is the Deep Neural Decisions Trees one. As turbulence and incertitude in financial markets have greatly expanded, machine learning algorithms are fairly relevant for the analysis of financial markets and, in specific, of the sovereign risk premium. Machine learning is notably helpful in dealing with problems that are not explicitly amenable to an analytical solution, like sophisticated categories techniques or trend recognition (Ghoddusi et al., 2019). Machine learning algorithms have been extensively employed in a diversity of computational issues (price forecasting, data analysis, and macro/micro-trend forecasting, demand prediction, risk administration, bargaining power) that often confront the challenge of the condition known as the curse of dimensionality (De Spiegeleer et al., 2018). Specifically, financial data analysis is a development challenge that scientists have had to face and financial markets have placed an acute call for the necessity to provide new models to enhance the comprehension of financial assets. Thus, Rundo et al. (2019) concluded that the implementation of machine learning techniques is advantageous in the area of quantitative finance, as it can perform analysis of a great amount of information in a limited amount of time and focus on empirical data and develop models grounded in the real market. On the one hand, Deep learning (DL) is a branch of machine learning techniques that relies on the use of inputs to provide training for a prediction model based on new inputs. In particular, DL methodology offers an efficient way to address financial market challenges, which differs from traditional applications of deep learning. For this reason, deep learning tools can be beneficial in these selection problems, as DL techniques provide the best solution to estimate whatever function maps the data into the value of the payoff (Rundo et al., 2019). Several researchers have applied DL in various areas of finance, such as financial market forecasting (Patel et al., 2015; Chen et al., 2015; Hafezi et al., 2015; Fischer & Krauss, 2018). They concluded that the advantage of this method over the ones given by classical statisticians and econometricians is that DL can manipulate a vast amount of unstructured and organised information and deliver fast predictions or conclusions. Furthermore, Sirignano and Cont (2019) demonstrate the feasibility and utility of DL methods for analysing intraday financial market behaviour, as they provide key knowledge about the essence of price formation in financial markets. On the other hand, several examples of the application of the fuzzy approach in building engineering and administration were listed in the work of Fayek (2020), such as construction labor productivity prediction, skills and performance of the project and the organisation, predicting productivity at the project level and conducting hazard assessments. Besides, the great achievement of fuzzy logic in remote monitoring has facilitated its use in numerous other domains, including the financial field. Sánchez-Roger et al. (2019) concluded that the fuzzy approach provides a powerful framework for application in finances owing to the fuzzy method's capability to deal with inaccurate, missing, and incomplete data.

We make at a minimum three additional contributions to the literature. First, we take into account a collection of all the explanatory variables applied in the previous literature for the analysis of sovereign risk premium behaviour in developed and emerging countries. We include behavioural factors as an economic sentiment indicator, consumer sentiment indicator, business confidence indicator, consumer confidence indicator, and Volatility Indicator (VIX). Concerning the common behavioural indexes used in the analysis, VIX is regarded by traders as one of the leading indices of market sentiment and investor risk tolerance among foreign traders. (Aristei & Martelli, 2014). It has important implications for policymakers, who must develop adequate government risk policies, aimed at reforming institutions to guarantee the sustainability of financial stability (Mpapalida & Malikane, 2019; Chen & Reitz, 2020; Corradin & Schwaab, 2023). Therefore, policymakers need to control the main factors that contribute to a country's risk. Second, we apply six methodologies, Fuzzy Decision Trees, Fuzzy Rough Nearest Neighbour, Neuro-Fuzzy Approach, Deep Neural Decision Trees, Deep Recurrent Convolution Neural Networks, and Deep Learning Linear Support Vector Machines, and have not been employed as a whole in previous research, obtaining very precise results. Most of the previous research has applied statistical methods, especially the regression model. Third, our study has analysed the sovereign risk premium globally, as an increasing number of papers deal specifically with the Eurozone, of interest to policymakers in economies all over the world.

This study is organised as described below: Section 2 offers an extensive overview of the literature on current empirical research on the sovereign risk premium. Section 3 presents the methodology employed. Section 4 provides the variables and data involved in the research. Section 5 discusses the findings achieved. The paper ends with the conclusions of the research and its recommendations.

2. Literature review

The existing literature on sovereign risk premiums to analyse sovereign risk premium behaviour in developed countries is scarce (Ciżkowicz et al., 2022; Gilchrist et al., 2022; Özmen, 2019; Cathcart et al., 2020; Orlov, 2019; Thornton & Vasilakis, 2017; Bi, 2012), but especially in European countries (Della Corte et al., 2023; Boitan & Marchewka-Bartkowiak, 2022; Kadiric, 2022; Cecchetti, 2020; Fontana & Langedijk, 2019; Augustin et al., 2020; Seoane, 2019; Palić et al., 2017; Bianchi, 2016; Aristei & Martelli, 2014; Iara & Wolff, 2014). Kadiric (2022) examines recent changes in the British and European government bond markets in relation to the UK's choice to exit the European Union. The findings indicate that the Brexit referendum had a notable effect on yield spreads, resulting in increased sovereign risk premiums in the UK and several other chosen Euro Area nations. On their side, Boitan and Marchewka-Bartkowiak (2022) examine the influence of various climate change metrics on the expense of government borrowing, indicated through sovereign bond yields and sovereign risk premiums, in a group of European Union nations spanning from 2000 to 2020. They conclude that climate change will exert a growing influence on the sovereign debt market.

On the other hand, a vast amount of researchers, have analysed the risk premium in emerging economies (Gilchrist et al., 2022; Bizuneh & Geremew, 2021; Arellano et al., 2020; Hofmann et al., 2020; Malliaropulos & Migiakis, 2018; Balima et al., 2017; Stolbov, 2017; Badaoui et al., 2016; Erdem & Varli, 2014; Martínez et al., 2013; Gumus, 2011). Özmen (2019) finds that developing economies' bond yields and Credit Default Swap premiums are more vulnerable to government borrowing, current account, and GDP enlargement than developed (eurozone) countries, indicating that financial markets are more sensitive to amendments in fiscal and current account shifts in developing countries.

On another side, considering the independent indicators, the ones most commonly reported in the literature to study the behaviour of the sovereign risk premium have been macroeconomic variables, such as Total Public Debt to GDP, Industrial Production, Trade Openness, GDP growth, Current account balance to GDP, Inflation rate (Boitan & Marchewka-Bartkowiak, 2022; Bizuneh & Geremew, 2021; Özmen, 2019; Mpapalida & Malikane, 2019; Fontana & Langedijk, 2019; Orlov, 2019; Doshi et al., 2017; Bianchi, 2016). Bizuneh and Geremew (2021) discover that the Covid-19 pandemic primarily affects sovereign risk premiums through GDP growth and indicators of political stability. Furthermore, their findings reveal that the real exchange rate and the net export to GDP ratio have a statistically significant influence on sovereign bond risk premiums.

There are also financial variables in the latest literature, including Foreign Exchange reserves, Real Effective Exchange Rate Indicator, CBOE Volatility Index, and S&P Indicator (Della Corte et al., 2023; Mpapalida & Malikane, 2019; Özmen, 2019; Orlov, 2019; Seoane 2019; Tkalec et al., 2014; Aristei & Martelli, 2014). Other financial variables are utilised in a variety of research studies, such as Money Supply, Banking crisis, and Currency crisis (Mpapalida &

Malikane, 2019; Di Cesare et al., 2012). For their part, Aristei and Martelli (2014) focus their research on the effect of behavioural drivers and expectations of the market, with the variables Consumer Sentiment Index, Economic Sentiment Indicator, Business Confidence Indicator, Consumer Confidence Indicator, and Business Climate Indicator. Finally, Özmen (2019) introduces political variables such as Government effectiveness and Rule of law. Among them, Mpapalida and Malikane (2019) determine that the variables Public debt to GDP, GDP enlargement, inflation rate, and foreign exchange reserves have a very relevant role to play in influencing the sovereign risk premia. Seoane (2019) showed that an income volatility rise may drive a rise in the likelihood of default and, consequently, could drive lower debt prices and higher sovereign spreads. Della Corte et al. (2023) reveal a fresh element for forecasting exchange rates, derived from the variance in price between sovereign credit default swaps expressed in varying currencies. This novel predictive factor, known as the credit-derived risk premium, encapsulates the anticipated devaluation of currency, contingent on a significant yet infrequent credit incident. They find that the credit-derived risk premium emerges as a pivotal influencer of exchange rate returns, and they furnish proof that investors can derive advantage from this fresh fount of information.

Analysing the methodology applied, a great number of studies have used statistical models for the analysis of the risk premium, highlighting Vector Autoregressions (VAR) (Cathcart et al., 2020; Palić et al., 2017; Bianchi, 2016), regression models (Kadiric, 2022; Boitan & Marchewka-Bartkowiak, 2022; Gilchrist et al., 2022; Bizuneh & Geremew, 2021; Arellano et al., 2020; Hofmann et al., 2020; Özmen, 2019; Orlov, 2019; Malliaropulos & Migialis, 2018; Konopczak & Konopczak, 2017; Lee et al., 2017a; Di Cesare et al., 2012) and Vector autoregression with stochastic volatility (Bi, 2012). By employing panel regressions and local projection analysis, Gilchrist et al. (2022) ascertain that an escalation in global financial risk results in a significant and enduring expansion of sovereign bond spreads. These impacts are most pronounced when gauging global risk using the excess bond premium – a gauge of the risk-bearing capability of US financial intermediaries. The transmission of global financial risk's effects is more noticeable for sovereign bonds with speculative-grade ratings. For their part, Zenios et al. (2021) apply a multi-period stochastic programming model on the scenario tree an efficient and flexible instrument for the assessment of debt stability and produce an abundant landscape for additional relevant investigation and policy inquiries.

On the other hand, the authors Augustin et al. (2020) develop the Bayesian Markov Chain Monte Carlos method. Among them, Palić et al. (2017) conclude that the VAR panel serves to investigate if short-term varies in the main economic variables can control the variation in the country risk prima and to inspect if changes in the variance of government spreads can affect real economic results. Cathcartt et al. (2020) also use the VAR model to check the effect of media content on sovereign credit risk. They apply panel VAR versus traditional VAR models, allowing the assumption of cross-sectional heterogeneity instead of cross-sectional homogeneity. These authors confirm that using the VAR panel, news sentiment could as well forecast the risk of default and the parts of the risk premium. For its part, Bi (2012) uses the dynamic stochastic general equilibrium structure, which is a non-linear and dynamic model, and concludes that this model allows analyzing, on the one hand, if the maximum level of debt that the Government can service can be based on macroeconomic fundamentals and, on the other hand, the quantitative impact of government default risk on the economy. Özmen (2019) proposes to analyze the repercussions of economic complexity on the sovereign risk premium with regression models, concluding that it has a significantly negative impact, and, therefore, with this model, it is determined that the capacity of an economy to produce goods Complexes could serve as an index of the economy's resilience to shocks and thus help turn down a country threat. Lastly, Konopczak and Konopczak (2017) conclude that their findings largely contradict prior literature, claiming that in the long run running demand-driven downward coercion on bond yields that derive from inflows of capital to developing countries may be saturated by an upward constraint on the government risk premia as a mirroring of over-reliance on outer finance. These authors determined that the method used in previous research has not completely captured the long-term effects. Table 1 displays a synopsis of this literature.

Table 1. Literature summary

Authors	Year	Countries	Methodology
Arellano et al.	2020	Emerging countries	Regression model
Aristei & Martelli	2014	European countries	Econometric method
Augustin et al.	2020	European countries	The Bayesian Markov Chain Monte Carlo (MCMC) method
Bi	2012	Developed countries	Vector autoregression with stochastic volatility
Bianchi	2016	Euro area countries	Vector autoregressive model
Bizuneh & Geremew	2021	Emerging countries	Regression model
Boitan & Marchewka-Bartkowiak	2022	European countries	Regression model
Cathcart et al.	2020	Developed countries	Vector autoregressive model
Cecchetti	2020	European countries	Econometric model
Di Cesare et al.	2012	Euro area countries	Regression model
Fontana & Langedijk	2019	European countries	Regression model
Gilchrist et al.	2022	Emerging and developed countries	Regression model
Hofmann et al.	2020	Emerging countries	Regression model
Kadiric	2022	Euro area countries	Ordinary Least Squares
Malliaropulos & Migiakis	2018	Emerging countries	Regression model
Mpapalida & Malikane	2019	African countries	Regression model
Orlov	2019	Advanced economies	Regression model
Özmen	2019	Advanced economies	Regression model
Palić et al.	2017	European countries	Vector autoregressive model
Seoane	2019	European countries	Regression model
Thornton & Vasilakis	2017	Advanced economies	Regression model

3. Methods

3.1. Fuzzy decision trees

In this method, we use the C4.5 algorithm, which is an expansion of the ID3 algorithm. It can be utilised to set up a decision tree in compliance with the elements that are in shorter subdivisions, in which the action of constructing a decision tree or rule is dependent on the choice to derive a value from the data (Rawal & Agarwal, 2019). In general, C4.5 is built in the order: a) sorting out features as the root; b) forming a root for every attribute; and c) reiterating the action for each root till all instances of the branches have the identical type. The largest profit is utilised for feature selection for root attributes, according to formula (1):

$$\text{Gain}(S, A) = \text{Entropy}(S) - \sum_{i=1}^{n} \frac{|S_i|}{|S|} = \text{Entropy}(S), \tag{1}$$

whereas S is the collection of examples, A are the features, n is the split value of feature A, and S_i is the total amount of occurrences in the i-th split. In turn, the Entropy value is given by formula (2).

$$\text{Entropy}(S) = \sum_{i=1}^{n} - p_i * log_2 * p_i \tag{2}$$

being p_i the S proportion.

Fuzzy decision trees follow the same basic structure as decision trees. These fuzzy decision trees simultaneously permit data to monitor several different branches of a unit node at differing levels of compliance in the interval (0–1) (Lee et al., 2017b; Prashanth et al., 2018; Hamrouni & Chaoui, 2022).

The FuzzyDT algorithm is constructed using the following steps. First, it identifies the fuzzy database, that is, the fuzzy granulation for the domains of the continuous features. 2. Substitute the training set continuous attributes with linguistic labels from the fuzzy sets having the best matching with the input values. 3. Compute the entropy and information gathering of every feature to divide the training set and determine the test tree nodes until all the features are utilised or all the training samples are sorted. 4. Perform a post-pruning procedure, similar to C4.5, utilising confidence bounds of 25–30%.

3.2. Fuzzy Rough Nearest Neighbour (FRNN)

The fuzzy K-nearest neighbour algorithm (Keller et al., 1985) was implemented to categorise testing items according to their closeness to a certain number of K of neighbours, and the levels of membership of these neighbours to the class tags (fuzzy or crisp). For the application of Fuzzy nearest neighbour, the degree $C''(y)$ that an unsorted item y pertains to a class C is calculated as:

$$C''(y) = \sum_{x \in N} R(x, y) C(x), \tag{3}$$

whereas N is the collection of the K nearest neighbours of the object y, derived by computing the fuzzy sameness among y and all training items and selecting the K items that exhibit the greatest level of resemblance. $R(x, y)$ is the value [0,1] of the relatedness between x and y. In the conventional method, it is fixed in the next form:

$$R(x,y)=\frac{\left\|x-y\right\|^{-2/(m-1)}}{\sum_{j\in N}\left\|y-j\right\|^{-2/(m-1)}}. \tag{4}$$

Denoting ||·|| the Euclidean standard, and m is a controlling parameter for the global equalisation weighting.

Besides, we suggest a fuzzy-rough nearest neighbours (FRNN) algorithm in which the closest neighbourhoods are utilised to build the fuzzy bottom and top approaches of the decision types, and the probe items are categorised according to their affiliation to such fuzzy proximities. The algorithm depends on the selection of a fuzzy tolerant function R. We define R as below: The whole range of requirements features A, R is given by

$$R(x,y)=\min_{a\in A}R_a(x,y) \tag{5}$$

being $R_a(x, y)$ the level of similarity between the items x and y for attribute a. There are many possible solutions, here we select

$$R_a(x,y)=1-\frac{\left|a(x)-a(y)\right|}{a_{\max}-a_{\min}}. \tag{6}$$

The FRNN algorithm's foundation consists in the fact that the bottom and top approach of a class of decision, computed using the closest neighbourhoods of a test object y, gives useful hints for forecasting the test object's membership in that class. Specifically, if $(R{\downarrow}C)(y)$ is large, it indicates that all neighbours of y are in C, and a great figure of $(R{\uparrow}C)(y)$ signifies that one neighbour at minimum is in that class.

To undertake crisp sorting, the algorithm produces the matched class decision with the best possible combination of fuzzy bottom and top proximity participants That is just one form of using the data from the bottom and top fuzzy approaches to establish class ownership, other forms are available but are not explored in this work. The algorithm complexity is O(|C|.(2|X|)).

3.3. Neuro-Fuzzy Approach (NFA)

We can employ simple supervised learning in a functional estimation problem, as the right exit for the training data is well-known. When utilising a fuzzy rule structure to approach the function, we can utilise the previous knowledge. This implies that if we are already aware of the appropriate rules for particular fields, we may start the neuro-fuzzy system with these rules. The rest of the rules must be discovered through learning. Without any previous knowledge, we begin with a Neuro-Fuzzy function approximator (NEFPROX) system that has no occult units, and we progressively start to learn all the rules.

The NEFPROX learning algorithm is shown in definition 3. We suppose triangular belonging operations are employed, which are expressed using three components

$$\mu:\mathbb{R}\to[0,1],\ \mu(x)=\begin{cases} {x\perp a}/{b\perp a} \text{ if } x\in[a,b), \\ {c\perp x}/{c\perp b} \text{ if } x\in[b,c,], \\ o \text{ otherwise.}\end{cases} \tag{7}$$

The membership functions further to the left and further to the right of every variable that can lie on shoulders. We employ triangular fuzzy ensembles for brevity, although the training algorithm may be extended to cover other types of membership features too. We may for instance employ the centre of gravity or the mean of the maximal methodology for defuzzification at the exit nodules.

To begin the training procedure, we need to identify the starting fuzzy sets for each input variable. For output variables, this is not required, where fuzzy partitions could be generated during the learning process. Nevertheless, when the fuzzy sets are to be used as the starting point of the learning algorithm, the fuzzy set can be settled. In case no fuzzy assemblies are provided, it is needed to determine the start width of an ownership function generated while learning.

The following definition 1 represents the departure from a NEFPROX unit.

Definition 1: Given a NEFPROX system with n inputs units $x_1, \ldots, x_n$, k rules units $R_1, \ldots, R_k$ and m output units $y_1, \ldots, y_m$ Considering a learning problem $\tilde{\mathcal{L}} = \left\{\left(s_1, t_1\right), \ldots, \left(s_r, t_r\right)\right\}$ or r patterns, each comprising an entry-level standard $s \in \mathbb{R}^n$, and a target standard $t \in \mathbb{R}^m$. The learning algorithm for generating the k units of rules for the NEFPROX systems includes the next stages:

2. Choose the upcoming pattern (s, t) from $\tilde{\mathcal{L}}$.

3. For every entrance unit $x_i \in U_1$ determine the composition operation $\mu_{ji}^{(i)}$ so that,

$$\mu_{ji}^{(i)}\left(s_i\right) = \max_{j \in \{1,\ldots,p_i\}} \left\{\mu_{ji}^{(i)}\left(s_i\right)\right\}. \tag{8}$$

4. In absence of guideline node R with

$$W\left(x_1, R\right) = \mu_{ji}^{(1)}, \ldots, W\left(x_n, R\right) = \mu_{jn}^{(n)} \tag{9}$$

so build such a node, and link it to all exit nodes.

5. For every link from the new node of the rule to the exit nodes, locate an appropriate fuzzy weight using the procedure below:

Based on the belonging functions attached to a unit of output y_i, determine a belonging function $v_{ji}^{(i)}$ so that

$$v_{ji}^{(i)}\left(t_i\right) = \max_{j \in \{1,\ldots,q_i\}} \left\{v_j^{(i)}\left(t_i\right)\right\}, \text{ and } v_{ji}^{(i)}\left(t_y\right) \geq 0.5. \tag{10}$$

If no such fuzzy set exists, then make $v_{new}^{(i)}$ so that $v_{new}^{(i)}\left(t_i\right) = 1$, joins it to the fuzzy sets associated with the output variable y_i, and set $W\left(R, y_i\right) = v_{new}^{(i)}$.

6. In case there are patterns still missing in $\tilde{\mathcal{L}}$, proceed to step (i), if not, cease making regulations.

7. Lastly, assess the base of rules. Find the mean output for each output variable of every rule with a level of compliance higher than 0. In case there is an exit fuzzy set, having the mean output a greater level of ownership than the actual fuzzy set utilised by the regulation in question, replace the resultant of the guideline correspondingly.

The fuzzy set supervised learning algorithm for a NEFPROX structure cycles over the learning set $\tilde{\mathcal{L}}$ with the next steps repeated till some stopping criteria are fulfilled:

1. Choose the following pattern (s,t) from $\tilde{\mathcal{L}}$, spread it across the structure x, and define the exit vector.
2. For every exit unit y_i, identify the gap between the target and current output value $\delta_{yi} = t_i \perp o_{yi}$.
3. For every rule unit R with $o_R > 0$:
   a) For everyone $y_i \in U_3$ define the changes for the settings a,b, and c of the fuzzy set $W(R, y_i)$ employing the learning rate $\sigma > 0$.

   When $W(R, y_i)(t_i) > 0$

$$\begin{aligned} \Delta_{b_i} &= \sigma.\delta_{yi}.(c \perp a).o_R.(1 \perp W(R, y_i)(t_i)), \\ \Delta_{a_i} &= \sigma.\,(c \perp a).o_R + \Delta_{b_i}, \\ \Delta_{c_i} &= \perp \sigma.\,(c \perp a).o_R + \Delta_{b_i}. \end{aligned} \tag{11}$$

   In case $W(R, y_i)(t_i) = 0$

$$\begin{aligned} \Delta_{b_i} &= \sigma.\delta_{yi}.(c \perp a).o_R.(1 \perp W(R, y_i)(t_i)), \\ \Delta_{a_i} &= \text{sgn}\,(t_i \perp b_i).\sigma.(c \perp a).o_R + \Delta_{b_i}, \\ \Delta_{c_i} &= \text{sgn}\,(t_i \perp b_i).\sigma.(c \perp a).o_R + \Delta_{b_i}. \end{aligned} \tag{12}$$

   Implement modifications to $W(R, y_i)$ unless this does not infringe on a certain set of restrictions Φ.

   b) Define the error of the regulation

$$E_R = o_R(1 \perp o_R).\sum_{y \in U_3} (2W(R, y_i)(t_i) \perp 1).|\delta_y|. \tag{13}$$

   c) For every fuzzy set $W(x, R)$ with $W(x, R)(o_x) > 0$ define the changes for its settings a,b,c employing the learning rate σ > 0:

$$\begin{aligned} \Delta_b &= \sigma.E_R.(c \perp a).(1 \perp W(x,R)(o_x)).\text{sgn}(o_x \perp b), \\ \Delta_a &= \perp \sigma.E_R.(c \perp a).(1 \perp W(x,R)(o_x)) + \Delta_b, \\ \Delta_c &= \sigma.E_R.(c \perp a).(1 \perp W(x,R)(o_x)) + \Delta_b \end{aligned} \tag{14}$$

   and implement modifications to $W(x, R)$ unless this does not infringe on a certain group of restrictions Φ.
4. In case an era has been reached, and the stop condition is satisfied, then it ceases, else it proceeds to setp (i).

As in the case of the NEFCLASS model (Nauck & Kruse, 1997), the rule learning algorithm chooses the fuzzy rules according to a prespecified partition of the input domain. This partition is provided by the initial fuzzy ensembles. When the algorithm generates excessive rules, it is viable to evaluate the rules by identifying the errors of the individual regulations, retaining just the good ones.

Nevertheless, the performance of the approach may be affected. Every rule stands for several exhibitions of the feature in the shape of a fuzzy exhibition. If the regulations are removed, this implies that certain sampling is no longer taken into account. If parametric learning is unable to offset this, the performance of the approximation must decline. For ranking problems, as managed by NEFCLASS (Nauck & Kruse, 1997), rule pricing is not a big problem. This is because of the "winner-takes-all" approach, not greatly affected by minor adjustments to the output units. In the contrary, the issue of NEFPROX is considered as an outcome operation so that shifts in the output units are more influential.

Like in our other neuro-fuzzy models NEFCON and NEFCLASS (Nauck et al., 1997), the process of learning fuzzy sets is a mere heuristic. It yields the displacement of the ownership functions and the increase or decrease of their supports. Like before, the learning process has to fulfil some restrictions Φ. An error can be chosen as a stopping criterion on a further validation set. Training continues till the error is no more falling. This is a technique in neural network learning and is employed to prevent overfitting of the training data.

3.4. Deep Recurrent Convolution Neural Network (DRCNN)

Recurrent neural networks (RNN) have been implemented in various forecasting areas owing to their enormous forecasting efficiency. The prior computations performed are what form the output within the RNN structure (Wang et al., 2017). For an entry sequence vector x, the hidden nodes of a coating s, and the output of a shadow coating y, could be computed as shown below.

$$s_t = \sigma\left(W_{xs}x_t + W_{ss}s_{t-1} + b_s\right); \tag{15}$$

$$y_t = o\left(W_{so}s_t + b_y\right), \tag{16}$$

whereas W_{xs}, W_{ss}, and W_{so} are the input coating weights x to the shadow coating s, by are the distortions of the shadow coating and the output coating. Formula (17) points out σ and o are the launch operations.

$$STFT\left\{z(t)\right\}(\tau,\omega) = \int_{-\infty}^{+\infty} z(t)\,\omega\left(t-\tau\right)e^{-j\omega t}dt\Big), \tag{17}$$

whereas $z(t)$ is the oscillation signs, $\omega(t)$ is the Gaussian window operation centred about 0. $T(\tau, \omega)$ is the operation that expresses the vibration signs. To compute the convolutional operation hidden layers, equations Eqs (18) and (19) are applied.

$$S_t = \sigma\left(W_{TS} * T_t + W_{SS} * S_{t-1} + B_s\right); \tag{18}$$

$$Y_t = o\left(W_{YS} * S_t + B_y\right) \tag{19}$$

being W the convolution kernels.

A recurrent Convolutional Neural Network (RCNN) can be stacked to set up a profound structure, named deep recurrent convolutional neural network (DRCNN) (Huang & Narayanan, 2017). To employ the DRCNN methodology in the task of prediction, Eq. (20) defines the last stage of the network as a monitored machine learning layer.

$$\hat{r} = \sigma\left(W_h * h + b_h\right), \tag{20}$$

W_h is the weight and b_h is the bias. The model estimates waste driven by the discrepancy between the planned and current findings in the trained phase (Ma & Mao, 2019). We apply stochastic gradient drop for the optimisation to apprehend the benchmarks. Taking the data at time t to be r, the residual operation is set as given in formula (21).

$$L(r,\hat{r}) = \frac{1}{2}\left\| r - \hat{r}_2^2 \right\|. \tag{21}$$

3.5. Deep Neural Decision Trees (DNDT)

Deep neural decision trees are Decision Tree (DT) modelling conducted by deep learning neural networks, in which a DNDT weight allocation matches a decision tree specified and is therefore predictable (Yang et al., 2018). The settings are fully optimalised with steep stochastic slope decay as opposed to a complex process of covetous partitioning; this enables a wide range computing with mini-batch-based learning and may be coupled to any bigger neural network (NN) model for deep end-to-end learning with forward reverse spread. In addition, standard DTs learn by greedy, resourceful feature partitioning (Quinlan, 1993). This ravening search can transform inefficiently, although this can have benefits for function selection (Norouzi et al., 2015). To predict the error rate of every node, the algorithm starts with an implementation of a smooth binning function that allows for split DNDT decisions (Dougherty et al., 1995). In the main, the input to a binning operation is a real scalar x that produces an indicator of the bins to which x is in. We suppose that x is a continuous variable, it is binned into n+1 intervals. This needs cut-off points that are qualified variables in this scene. The cut-off points are given as (β_1, β_2, ..., β_n) and are strictly upwards so that $\beta_1 < \beta_2 < \ldots < \beta_n$.

The activation operation of the DNDT algorithm is deployed as below in Eq. (22):

$$\pi = fw, b, \tau(x) = \text{softmax}\left(\left(wx + b\right) / \tau\right) \tag{22}$$

being w a constant with value w = [1, 2, ..., n + 1], $\tau > 0$ is a temperature factor, and b is given in Eq. (23).

$$b = [0, -\beta_1, -\beta_1, -\ \beta_2 \ldots, -\beta_1 - \beta_2 - \ldots - \beta_n]. \tag{23}$$

Besides, if τ leans to 0, the vector sampling is settled by employing the Straight-Through (ST) Gumbel–Softmax method (Ho, 1998).

Taking in account the binning operation as detailed above, the target is to construct the DT employing the Kronecker product. We suppose we have an input instance $x \in R^D$ with D features. Linking every feature x_d with its NN $f_d\left(x_d\right)$, we can establish all the final nodes of the DT, as in Eq. (24).

$$z = f_1\left(x_1\right) \otimes f_2\left(x_2\right) \otimes \ldots \otimes f_D\left(x_D\right), \tag{24}$$

whereas z is a vector that designates the indicator of the leaf node gained by instance x. We suppose that a linear classifier on every leaf z ranks the attained levels. Per feature, the cut-off point number is the model's complexity measure. The values of the cut-off points are unlimited, denoting that certain cut-off points may be missing. For instance, they are shorter than the minimal x_d or higher than the maximal x_d.

3.6. Deep Learning Linear Support Vector Machines (DSVM)

Linear support vector machines (SVM) are drawn for binary ranking (Alaminos et al., 2022). Having training data and stickers $\left(x_n, y_n\right), n = 1,\ldots,N, x_n \in \mathbb{R}^D, t_n \in \{-1,+1\}$, SVMs learning is based on the constrained optimization defined in Eq. (25).

$$\min_{w\xi_n} \frac{1}{2} W^T W + C\sum_{n=1}^{N} \xi_n, \tag{25}$$

$$\text{subject to } W^T x_n t_n \geq 1 - \xi_n > \forall n,$$

$$\xi_n \geq 0 \ \forall n,$$

where ξ_n are slack variables that punish those that infringe on the margin requisites. We can add the bias by incrementing all data vectors x_n with a value of 1. The dissipated optimization problem is shown in Eq. (26).

$$\min_{w} \frac{1}{2} W^T W + C\sum_{n=1}^{N} \max\left(1 - W^T x_n t_n, 0\right). \tag{26}$$

If there is any classification problem when using deep learning techniques, it is usual to employ the softmax or 1-of-K encoding at the top. For instance, if we have 10 possible classes, the softmax cape has 10 nodes marked by p_i , where i = 1, . . . , 10; p_i defines a disjoined likelihood placement, so, $\sum_{i}^{10} p_i = 1$.

If h is the activation of the next-to-last cape nodes, W is the weight linking the second last cape to the softmax cape, the total input into a softmax cape, as expressed in Eq. (27). Then, we obtained Eq. (28).

$$a_i = \sum_{k} h_k W_{ki}; \tag{27}$$

$$p_i = \frac{exp\left(a_i\right)}{\sum_{j}^{10} exp\left(a_j\right)}. \tag{28}$$

The forecast class $\hat{\imath}$ would be as given in Formula (29).

$$\hat{\imath} = arg\max_{i} p_i = arg\max_{i} a_i. \tag{29}$$

A popular DSVR variation is used as Linear-SVM is not differentiable, and the squared hinge loss is minimized as indicated in Formula (30).

$$\min_{w} \frac{1}{2} W^T W + C\sum_{n=1}^{N} \max\left(1 - W^T x_n t_n, 0\right)^2. \tag{30}$$

The DSVR aims to train deep neural nets for categorization. Shorter layer weights are learned by back-propagating the gradients from the top cape linear SVM (Alaminos et al., 2022). For it, we have to adapt the SVM aim about the activation of the penultimate layer. Let the goal in Eq. (31) be $l(w)$, and the input x is repositioned with the second last activation h.

$$\frac{\partial l(w)}{\partial h_n} = -Ct_n w\left(\mathbb{I}\left\{1 > w^T h_t t_n\right\}\right), \tag{31}$$

where $\mathbb{I}\{\times\}$ is the indicator operation. Besides, for the DSVR, we exhibit Formula (32).

$$\frac{\partial l(w)}{\partial h_n} = -2Ct_n w\left(\max\left(1 - W^T h_n t_n, 0\right)\right). \tag{32}$$

3.7. Sensitivity analysis

If there are many variables, it is convenient to quantify their impact, even though there is a high capacity for explaining the variables with these techniques. For this, the sensitivity analysis is carried out. The objective is to establish the importance of the independent variables with the dependent ones (Saltelli, 2002; Alaminos et al., 2020). It is about adding the models with the most important variables and eliminating those with the least important ones. One variable is more important than another if it rises the variance, contrasted to the group of variables of the model. The Sobol technique (Saltelli, 2002) is employed to degrade the variance of the total output $V(Y)$ given by the set of equations shown in (33).

$$V(Y) = \sum_i V_i + \sum_i \sum_j > \mathbb{I}V_{ij} + \ldots + V_{1,2,\ldots k}, \tag{33}$$

whereas $V_i = V(E(Y|X_i)$ and $V_{ij} = \mathrm{MV}(E(Y|X_i, X_j)) - V_i - V_j$.

For its part, the sensitivity indicators are established by $S_i = V_i/V$ and $S_{ij} = V_{ij}/V$, where S_{ij} means the impact of the interaction between two variables. The Sobol degradation permits the prediction of a total sensitivity indicator ST_i, measuring the total of all the sensitivity outcomes elaborated in the autonomous variables.

3.8. Research steps

Empirical research aimed at predicting sovereign risk premiums should follow a structured process involving five main stages. These stages include creating a sample, preprocessing the data, building the model, assessing accuracy, and carrying out classification and forecasting, as shown in Figure 1. To begin the process, the stage of creating a sample involves obtaining data from relevant sources such as publicly available information from international economic institutions. The dataset includes attributes related to macroeconomic variables, global variables, political factors, and financial variables. In the next stage of preprocessing the data, activities include categorising continuous attribute values, simplifying the data, analysing connections between attributes, and removing data points that are outliers. Moving on to the stage of constructing the model, the approach relies on learning from the preprocessed data, using algorithms outlined in Section 3. This process involves identifying the most in-

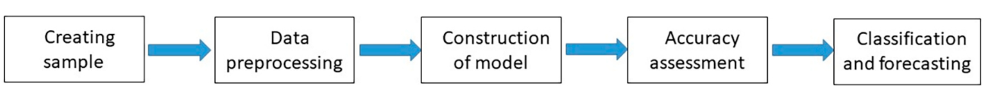

Figure 1. Flowchart of the Research (source: Own elaboration)

fluential independent variables. The sample is randomly divided into three separate sets: a training set (70%), a validation set (10%), and a testing set (20%). The cross-validation method is employed, using 10-fold and 500 iterations, following the approach of works such as Tsamardinos et al. (2018) and Salas et al. (2020), to estimate error rates. The first set is used to train the model and determine its parameters, the second set assesses each algorithm to prevent overfitting, and the third set evaluates prediction accuracy in the accuracy assessment phase. Finally, the stage of classification and forecasting evaluates the model's strength and its effectiveness in predicting sovereign risk premiums on a global scale.

4. Sample, data, and variables

A sample of 34 countries in the period from 1960 to 2021 is selected (11 developing countries and 23 advanced economies; see Appendix A–C), building 3 models (emerging, developed, and global) of sovereign risk premium. We have got data on the dependent and autonomous variables and for the classification of the countries from the IMF's International Financial Statistics (IFS), the World Bank, Eurostat, OCDE, and Fred Sant Louis. Regarding the computing power used for our estimations, we have used a two four-core Intel Core I7-6500U and the code has been made from MATLAB package (R2019b).

The dependent variable employed in the present research is a sovereign risk premium, which yields spreads concerning a country's sovereign bonds assumed as without risk. It has been computed as the difference between the interest rate paid on a country's government debt and the interest paid on the debt issued by the United States government (as a risk-free reference country), taking the 10-year bond as a reference.

Concerning the independent variables, we apply 26, which are classified into financial, macroeconomic, global, and political variables, as indicators that determine the relationship of these variables with the sovereign risk premium (Table 2). These variables have been employed all over prior literature (Fontana & Langedijk, 2019; Mpapalida & Malikane, 2019; Özmen, 2019; Orlov, 2019; Marshall & Elzinga-Marshall, 2017; Bianchi, 2016; Aristei & Martelli, 2014, Linciano et al., 2013; Comelli, 2012; De Grauwe & Ji, 2012; Siklos, 2011).

5. Results

Our results differentiate between global trend models and extreme events in the determinants of the sovereign risk premia to cover the isolated cases that the global pattern models cannot naturally capture. The extreme events process collects those moments of extremity, i.e. when the primary risk has undergone a larger and atypical variation concerning the average. Tables 3 and 4 show the results of precision estimated for emerging economies, advanced economies, and global, in overall patterns and extreme events respectively. Figures 2 and 3 exhibit the root mean square error (RMSE) in cases of global patterns and extreme events for each of them too. In the global pattern case the precision level overcomes at all times 84.05% and in extreme events exceeds 80.22%. Besides, RMSE has appropriate standards. The model with the greatest precision is that of advanced economies with 94.60%, come after by the model of developing markets with 92.57% in the position of global patterns, with the same

Table 2. Independent variables for the sovereign risk premium

Code	Description	Source	Expected Sign
Financial variables			
ER	Real Effective Exchange rate index	Fontana & Langedijk, 2019	–
FER	Foreign exchange reserves	Fontana & Langedijk, 2019	–
BC	Banking crisis	Linciano, Giordano & Soccorso, 2013	+
CCI	Currency crisis	Linciano, Giordano & Soccorso, 2013	+
M2/ GDP	Money Supply/GDP	Siklos, 2011	–
VIX	CBOE Volatility Index	Aristei & Martelli, 2014	+
SPI	S&P 500 Index	Özmen, 2019	–
Macroeconomic variables			
GDEBT	Total Public Debt/GDP (%gdp)	De Grauwe & Ji, 2012	+
SDC	Sovereign debt crisis	Linciano, Giordano & Soccorso, 2013	+
GDP	GDP growth (%)	Maltritz & Molchanov, 2013	–
IP	Industrial production (% GDP)	Linciano, Giordano & Soccorso, 2013	–
INFLA	Inflation rate	Comelli, 2012	+
TO	Trade Openness	Mpapalida & Malikane, 2019	–
T	Trade (% of GDP)	Mpapalida & Malikane, 2019	–
CA	Current Account Balance/GDP (%GDP)	Fontana & Langedijk, 2019	–
FS	Fiscal Space (sovereign debt/ tax revenues)	Linciano, Giordano & Soccorso, 2013	+
OP	Global Oil Price (West Texas Intermediate)	Siklos, 2011	–
Global variables			
CSI	Consumer Sentiment Index	Aristei & Martelli, 2014	–
ESI	Economic sentiment indicator	Aristei & Martelli, 2014	–
BCOI	Business Confidence indicator	Aristei & Martelli, 2014	–
CCI	Consumer Confidence indicator	Aristei & Martelli, 2014	–
BCI	Business Climate Index	Aristei & Martelli, 2014	–
Political variables			
PE	Political effectiveness(*)	Marshall & Elzinga-Marshall, 2017	–
EF	Economic effectiveness(*)	Marshall & Elzinga-Marshall, 2017	–
GE	Government effectiveness	Özmen, 2019	–
R	Rule of law	Özmen, 2019	–

Note: (*) 0 "no fragility", 1 "low fragility", 2 "medium fragility" and 3 "high fragility".

models coinciding with higher accuracies in the extreme event scenario with precisions of 91.99% and 90.91% respectively. Considering the global pattern scenario, in developing, advanced and global level, the biggest precision values for every model are found in the DNDT method, come after by the DSVM, with a scope of 94.60%–88.91%. Also for the three country models in the case of extreme values, the methodology with the biggest precision values is DNDT, but unlike the previous scenario, the second best accuracy is the DRCNN method, resulting in an estimated precision range of 91.99%–85.18%. So, if we make a comparison of the accuracy between our methodological techniques, we can find that the method with the biggest precision in determining the sovereign risk premium is DNDT, followed by DSVM and DRCNN. Finally, deep learning methods forecast the behaviour of the sovereign risk premium better than fuzzy approaches, although the latter has also obtained very good results, being the FDT technique the most precise among them. Anyhow, exactness is upper than 84.05% for determining the sovereign risk prima, and the RMSE values are not higher than 0.245, obtaining better results compared to previous literature. Thus, Malliaropulos and Migiakis (2018) reach RMSE levels of 0.356, and Cecchetti (2020) an RMSE amount of almost 0.364.

Table 3. Results of Precision Training: Global Patterns

Model	Dataset	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
Advanced	Training	90.27	89.84	88.96	91.76	95.87	94.10
	Validation	89.93	89.50	88.62	91.41	95.51	93.74
	Testing	89.08	88.65	87.78	90.55	94.60	92.85
Emerging	Training	88.33	87.91	87.05	89.79	93.81	92.08
	Validation	88.00	87.58	86.72	89.45	93.46	91.73
	Testing	87.17	86.75	85.90	88.60	92.57	90.86
Global	Training	87.29	86.87	86.02	88.73	92.70	90.99
	Validation	86.11	85.70	84.86	87.53	91.45	89.76
	Testing	85.30	84.89	84.05	86.70	90.58	88.91

Table 4. Results of Precision Training: Extreme Events

Model	Dataset	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
Advanced	Training	86.98	88.21	84.89	90.15	93.22	88.95
	Validation	86.65	87.88	84.58	89.81	92.87	88.62
	Testing	85.83	87.05	83.77	88.96	91.99	87.78
Emerging	Training	85.11	86.32	83.07	88.21	91.21	87.04
	Validation	84.79	85.99	82.76	87.88	90.87	86.71
	Testing	83.99	85.18	81.98	87.05	90.01	85.89
Global	Training	84.11	85.30	82.09	87.17	90.14	86.01
	Validation	82.97	84.15	80.98	86.00	88.92	84.85
	Testing	82.19	83.35	80.22	85.18	88.08	84.05

Furthermore, we incorporate an additional error metric, Absolute Percentage Error (MAPE), to offer a more comprehensive view of the precision of our models. MAPE offers a relative error measurement and can be valuable for evaluating the precision of predictions across various scales and within differing contexts. Figures 4 and 5 exhibit this new measure of error in cases of global patterns and extreme events for each of them. MAPE has adequate standards as it is below 5% in all cases, which is considered an indication that the forecast is acceptably accurate.

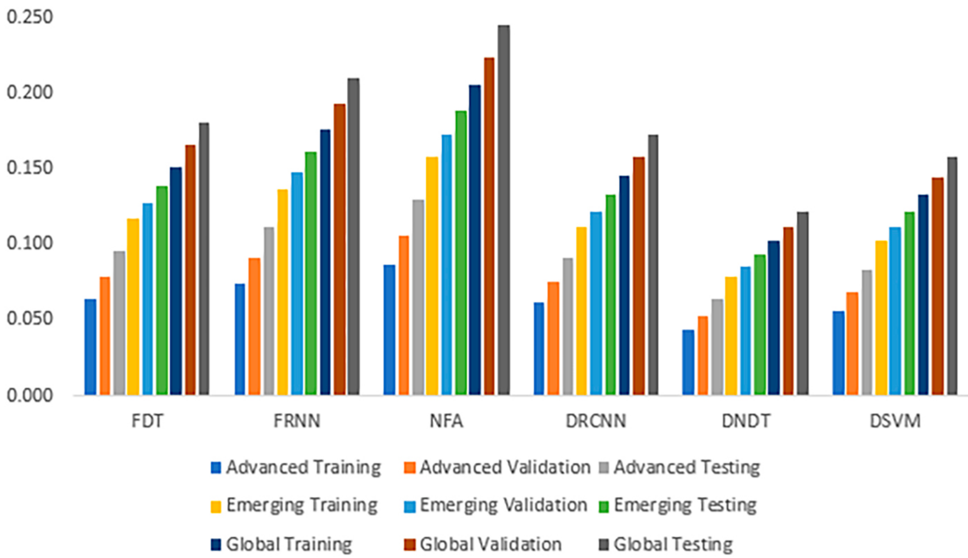

Figure 2. RMSE: Global Patterns

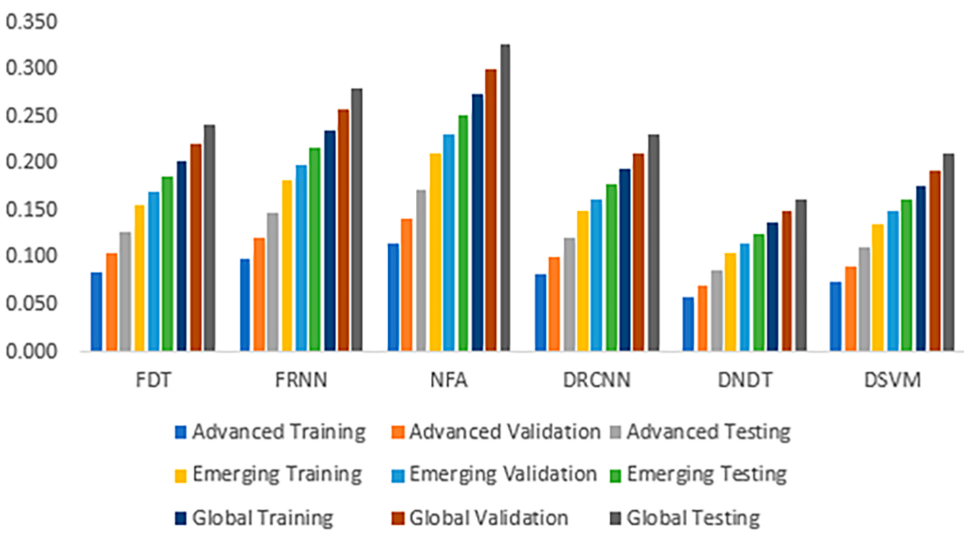

Figure 3. RMSE: Extreme Events

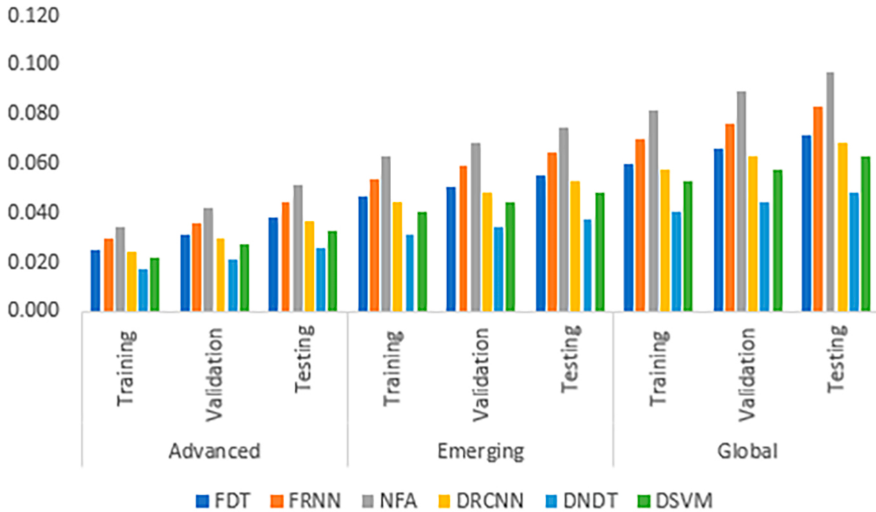

Figure 4. MAPE: Global Patterns

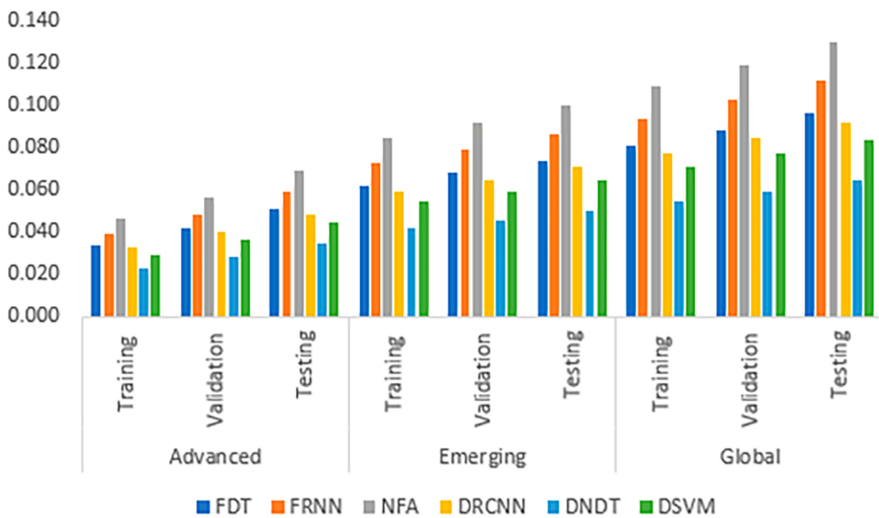

Figure 5. MAPE: Extreme Events

Tables 5, 6, and 7 display further information on the relevant variables in the case of the global pattern scenario in emerging, advanced, and global countries, separately. In addition, the most significant variables in the case of extreme events for emerging, advanced and global country samples are shown in Tables 8, 9, and 10 respectively.

Table 5. Significant variables emerging countries: Global Patterns

EMERGING	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
SDC	0.467	0.862	0.564	0.759	1.174	0.868
CCI	0.347	0.204	0.500	0.093	0.595	0.208
GDEBT	0.222	0.727	0.417	0.405	0.729	0.219
TO	0.474	0.780	0.421	0.736	0.821	0.351
FER	0.516	0.715	1.104	1.023	1.207	0.945
INFLA	0.149	0.206	0.049	0.412	0.492	0.219
M2/GDP	0.103	0.054	0.139	0.134	0.572	0.163
GDP	0.344	0.280	0.271	0.060	0.325	0.245
VIX	0.210	0.429	0.101	0.615	0.711	0.502
PE			0.291	0.390	0.138	0.103
R	0.382	0.558		0.168	0.122	
BCOI	0.690	0.782	0.421	0.318	0.258	0.607

Table 6. Significant variables advanced countries: Global Patterns

ADVANCED	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
SDC	0.645	1.149	0.983	1.247	1.317	1.051
GDEBT	0.818	0.792	1.007	0.961	1.082	1.030
TO	0.424	0.532	0.376	0.627	0.695	0.364
FER	0.138	0.513	0.274	0.326	0.519	0.346
M2/GDP	0.693	0.525	0.284	0.514	0.831	0.279
GDP	0.891	0.543	0.487	0.770	0.927	0.775
VIX	0.208	0.138	0.162	0.270	0.429	0.284
SPI	0.216	0.122	0.037	0.261	0.372	0.277
EF	0.142	0.141	0.311	0.200		0.078
CSI		0.117		0.367	0.214	
R	0.402	0.258	0.974	0.789	0.148	0.778

Table 7. Significant variables global countries: Global Patterns

GLOBAL	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
SDC	1.175	1.179	1.232	1.024	1.493	1.090
GDEBT	0.604	0.968	0.669	0.621	1.241	0.664
TO	0.630	0.400	0.562	0.422	0.852	0.702
FER	0.351	0.055	0.661	0.510	0.694	0.154
M2/GDP	0.586	0.079	0.194	0.302	0.701	0.005
GDP	0.317	0.693	0.831	0.297	0.937	0.819
VIX	0.025	0.387	0.210	0.024	0.583	0.532
PE	0.151	0.088	0.325		0.252	0.229
R	0.048	0.215	0.275	0.070	0.415	
BCOI		0.153	0.110	0.153	0.177	0.351

Table 8. Significant variables emerging countries: Extreme Events

EMERGING	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
SDC	1.172	1.013	0.935	0.947	1.174	1.140
CCI	0.026	0.491	0.433	0.217	0.595	0.106
GDEBT	0.380	0.237	0.459	0.260	0.729	0.129
TO	0.150	0.597	0.608	0.129	0.821	0.444
FER	1.116	0.959	1.060	0.719	1.207	1.078
INFLA	0.165	0.154	0.152	0.106	0.492	0.072
M2/GDP			0.084	0.516	0.572	0.003
GDP	0.012	0.320	0.318	0.124	0.325	0.041
VIX	0.107	0.686	0.553	0.059	0.711	0.593
PE	0.106	0.106	0.046		0.138	
R	0.874	0.801	0.927	0.539	0.122	0.658
BCOI	0.576	0.845	0.467	0.525	0.058	0.855
BC	0.514	0.465	0.651	0.649	0.139	0.336

Table 9. Significant variables advanced countries: Extreme Events

ADVANCED	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
SDC	1.286	1.029	1.171	0.692	1.317	1.271
GDEBT	0.905	0.640	0.980	0.417	1.082	0.809
TO	0.247	0.634	0.604	0.072	0.695	0.560
FER	0.251	0.148	0.504	0.136	0.519	0.468
M2/GDP	0.121	0.812	0.447	0.182	0.831	0.730
GDP	0.606	0.400	0.917	0.914	0.927	0.840
VIX	0.127		0.238	0.283	0.429	0.093
SPI				0.242	0.372	0.278
EF	0.088	0.109	0.022	0.102	0.152	0.076
CSI		0.101	0.112	0.124	0.214	
R	1.244	0.916	1.179	1.264	0.148	1.024
BC	0.646	0.973	0.316	0.342	0.311	0.165

Table 10. Significant variables global countries: Extreme Events

GLOBAL	FDT	FRNN	NFA	DRCNN	DNDT	DSVM
SDC	1.455	0.939	0.784	1.084	1.493	1.484
GDEBT	1.190	0.876	1.163	0.878	1.241	0.664
TO	0.377	0.455	0.225	0.446	0.852	0.401
FER	0.565	0.116	0.450	0.560	0.694	0.513
M2/GDP	0.361	0.626	0.644	0.327	0.701	0.697
GDP	0.651	0.354	0.867	0.267	0.937	0.529
VIX	0.014	0.036	0.460	0.429	0.583	0.499
PE		0.425	0.172		0.252	
R			0.129	0.127	0.415	0.046
BCOI	0.107	0.399		0.193	0.177	0.136
BC	0.031	0.340	0.130		0.257	0.129

The strongest results achieved in determining the sovereign risk premium have been in the DNDT approach and show that in a global pattern scenario, for emerging countries, FER, SDC, TO, GDEBT, VIX, CCI, and M2/GDP are the significant variables. On the other hand, the variables that best explain the extreme moments of the sovereign risk prima are the same as in the previous scenario. In comparison with prior studies, Mpapalida and Malikane (2019) find that GDEBT, GDP, INFLA, and FER are more relevant in fluencing the sovereign risk premia, but they have concluded that the majority of changes in the sovereign bond differential are described by GDP. This means that an increase in a country's overall economic performance brings the macroeconomic stability of fiscal variables and therefore reduces the likelihood of a sovereign default. For its part, Özmen (2019) concludes that the effect of CA and real GDP enlargement on risk premiums are explicative for developing countries, and gross government debt too. Siklos (2011) concludes that great GDP growth, higher reserves, and an arise in money supply reduce the government bond differential. So, our research has corroborated new explicative variables (SDC, TO, VIX, CCI, and M2/GDP), pointing out a new group of significant variables as opposed to what was displayed in prior research. VIX allows to representation of the uncertainty of the market in general and adequately controls the effect of investor expectations on short-term volatility in sovereign bond spreads. TO is directly correlated with GDP growth, and this suggested that enhancement in a country is linked with a small sovereign risk premium.

Concerning the results obtained in the sample of developed countries, for both global patterns and outliers, the most relevant variables for explaining the behaviour of the sovereign risk premium are SDC, GDEBT, GDP, M2/GDP, TO, and FER. Compared with recent work, Özmen (2019) establishes that INFLA and GDEBT stand out as explanatory variables in the sovereign risk prima for advanced economies. According to Tkalec et al. (2014), FER is a relevant variable in deciding the level of risk prima. The gathering of FER should decrease the country's risk, a low FER ratio engenders a high probability of sovereign default and cash risks. For its part, De Grauwe and Ji (2012) find that a big GDEBT raises the debt service cost, as well as the likelihood of a sovereign default. All this supports that our investigation has resulted in the identification of new meaningful variables (SDC, GDP, M2/GDP, and TO) identifying a novel group of important variables that differ from those reported in prior works. Large growth in GDP increases the debt servicing capacity of the country, leading to a decline in the risk premium rate. A sovereign debt crisis comes about if a country defaults on its bills, so the higher risk premium raises public borrowing costs and further raises sovereign debt, which again raises the risk premium.

Regarding the countries at a global level, we can be observed that the variables that best explain the extreme values of the sovereign risk premium, as well as in the overall pattern are SDC, GDEBT, GDP, TO, M2/GDP, and FER. In other papers, Malliaropulos and Migiakis (2018) demonstrate that Global volatility conditions are a relevant factor of sovereign differentials. In particular, the surge in world risk sentiment, as indexed by the VIX, is linked to a widening of spreads across rating grades. Other authors (Corradin & Schwaab, 2023; Tkalec et al., 2014; Maltritz & Molchanov, 2013), also find that the VIX plays an influential part in setting the differential of government bond spreads through time and provide evidence that the sovereign risk premia widen in reaction to elevated sentiment in the market. All of this concludes that our work has consolidated important new variables (SDC, GDEBT, GDP, TO, M2/GDP, and FER).

This study offers practical implications with strong relevance in the domain of financial risk assessment and decision-making, particularly in countering speculative practices. By comparing the effectiveness of fuzzy logic-based models with deep learning approaches, this research provides valuable insights for assessing sovereign risk premiums, a critical factor in the investment and financial sectors.

One significant application of this study pertains to portfolio management. Investment firms and asset managers can leverage the findings to fortify their risk management strategies, actively countering speculative activities. The insights gleaned from both fuzzy logic and deep learning models enable these professionals to make more enlightened decisions about portfolio diversification across various sovereign bonds, all the while considering global patterns and extreme events. This approach cultivates more resilient risk-adjusted returns and a heightened comprehension of potential vulnerabilities, particularly crucial during turbulent economic conditions when speculation may be rampant.

Additionally, this research empowers central banks and policymakers with a deeper understanding of the determinants influencing sovereign risk premiums. Armed with the identified models, they can gauge the potential repercussions of policy changes on these premiums, facilitating more accurate decisions for sustaining economic stability. This holds particularly significant implications for emerging economies aiming to attract foreign investments while prudently managing their exposure to sovereign risk, effectively mitigating speculative tendencies.

Furthermore, financial institutions and credit rating agencies can integrate the insights derived from this study into their risk assessment frameworks, a proactive measure against unwarranted speculation. These organizations can cultivate more precise and adaptive models for evaluating the creditworthiness of sovereign entities, yielding enhanced credit risk assessments, well-informed lending decisions, and more effective risk pricing for sovereign bonds. In this manner, the study contributes to a financial landscape that operates with greater transparency and reduced susceptibility to speculative forces.

6. Conclusions

This research has implemented new models to analyse the behaviour of the sovereign risk premium for developing markets, advanced countries, and a global sample of countries. We have compared fuzzy approaches with deep learning methods through 6 methodologies, FDT, FRNN, NFA, DRCNN, DNDT, and DSVM, not used in previous studies, obtaining very precise results. The level of accuracy in the sample in all six methods has been in a range between 94.60% and 84.05% in the global pattern scenario, and in the case of extreme events in a range between 91.99% and 80.22%.

In comparison with earlier investigations, this research study has been successful in considering a more complete set of variables in both advanced and emerging countries, and also at the global level, highlighting the variables SDC, M2/GDP, TO, VIX, and FER. This is an outstanding achievement in the area of cross-border finance. In the context of emerging nations, significant variables encompass FER, SDC, TO, GDEBT, VIX, CCI, and M2/GDP. When considering the outcomes gathered from the assortment of developed nations, for both global trends and anomalies, the key variables that offer insight into sovereign risk premium patterns are SDC, GDEBT, GDP, M2/GDP, TO, and FER. Variables of significance within emerging nations but not within developed nations comprise VIX and CCI, both of which are financial indicators. Conversely, variables that hold relevance within developed economies but not within developing economies are GDP and M2/GDP. The diversity of economic cycles, economic advantages, and production models between these regions leads to distinct predictors. For instance, emerging nations are more sensitive to balance of payments, accrued reserves, and currency instability. In contrast, developed nations often grapple with higher debt and external consumption concerns.

The limitations that could impact the understanding of our outcomes include the size of the sample utilised in our investigation, largely due to the absence of more frequent data and the unavailability of macroeconomic data. This challenge renders the meaningful analysis of sovereign bond premiums for both developing and developed nations challenging.

The findings are significant for policy-makers everywhere, as our research proposes meaningful new explicative variables for policy-makers to develop adequate government risk policies aimed at bringing about structural changes that would guarantee the stability and sustainability of financial markets and macroeconomic policy.

This work provides an excellent contribution to the area of Finance, in that the obtained findings may have significant consequences for the decisions of policymakers in the future, allowing them to avoid defaulting on their sovereign debt by failing to meet their interest or principal payments. The results obtained also allow these agents to alert the financial markets and prevent financial crises arising from changes in the sovereign risk premium.

Given all this, our analysis suggests that policymakers ought to focus more carefully on the variance movements of sovereign differentials. It follows from this study that failure in doing so could lead to permanent and adverse economic implications. Our work has major connotations for both risk-takers and policymakers, as it improves our ability to understand changes in the term structure of sovereign bond yield spreads. We believe our findings have relevance for both scholars and professionals and are of particular significance for policymakers in building a deeper comprehension of the feedback loops between the sovereign risk premium and government bond markets. Policies to enhance skills and create workplaces that allow for interaction and exchange of different skills will contribute to lower risk premia as the complexity of the economy increases.

Other extensions to this document could be the inclusion of the study of the contagion effect and its influence on the risk premium, as well as its correlation with the sustainability of government debt, in terms of the fiscal approach. In addition, other future lines of research may include the study of the particular factors that impact the forecasting of sovereign risk premiums in emerging nations, or exploring alternative models or methodological approaches to enhance the precision of predictions in the analysis of sovereign risk premium.

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References

Alaminos, D., Esteban, I., & Fernández-Gámez, M. A. (2020). Financial performance analysis in European football clubs. *Entropy*, *22*(9), Article 1056. https://doi.org/10.3390/e22091056

Alaminos, D., Salas, M. B., & Fernández-Gámez, M. A. (2022). Quantum computing and deep learning methods for GDP growth forecasting. *Computional Economics*, *59*, 803–829. https://doi.org/10.1007/s10614-021-10110-z

Andrade, S. C., Ekponon, A., & Jeanneret, A. (2023). Sovereign risk premia and global macroeconomic conditions. *Journal of Financial Economics*, *147*(1), 172–197. https://doi.org/10.1016/j.jfineco.2022.07.003

Arellano, C., Bai, Y., & Mihalache, G. P. (2020). *Monetary policy and sovereign risk in emerging economies* (*NK-default*) (Working paper No. w26671). National Bureau of Economic Research. https://doi.org/10.3386/w26671

Aristei, D., & Martelli, D. (2014). Sovereign bond yield spreads and market sentiment and expectations: Empirical evidence from Euro area countries. *Journal of Economics and Business*, *76*, 55–84. https://doi.org/10.1016/j.jeconbus.2014.08.001

Augustin, P., Boustanifar, H., Breckenfelder, J., & Schnitzler, J. (2018). Sovereign to corporate risk spillovers. *Journal of Money*, *Credit and Banking*, *50*(5), 857–891. https://doi.org/10.1111/jmcb.12497

Augustin, P., Chernov, M., & Song, D. (2020). Sovereign credit risk and exchange rates: Evidence from CDS quanto spreads. *Journal of Financial Economics*, *137*(1), 129–151. https://doi.org/10.1016/j.jfineco.2019.12.005

Badaoui, S., Cathcart, L., & El-Jahel, L. (2016). Implied liquidity risk premium in the term structure of sovereign credit default swap and bond spreads. *The European Journal of Finance*, *22*(10), 825–853. https://doi.org/10.1080/1351847X.2014.996297

Badarau, C., Huart, F., & Sangaré, I. (2014). Sovereign risk premium and divergent fiscal policies in a Monetary Union. *Revue d'économie politique*, *124*, 867–898. https://doi.org/10.3917/redp.246.0867

Baldacci, E., & Manmohan, K. (2010). *Fiscal deficits*, *public debt and sovereign bond yields* (IMF Working Paper WP/10/184). International Monetary Fund. https://doi.org/10.5089/9781455202188.001

Balima, W. H., Combes, J. L., & Minea, A. (2017). Sovereign debt risk in emerging market economies: Does inflation targeting adoption make any difference? *Journal of International Money and Finance*, *70*, 360–377. https://doi.org/10.1016/j.jimonfin.2016.10.005

Bi, H. (2012). Sovereign default risk premia, fiscal limits, and fiscal policy. *European Economic Review*, *56*(3), 389–410. https://doi.org/10.1016/j.euroecorev.2011.11.001

Bianchi, B. (2016). Sovereign risk premia and the international balance sheet: Lessons from the European crisis. *Open Economies Review*, *27*, 471–493. https://doi.org/10.1007/s11079-015-9382-8

Bizuneh, M., & Geremew, M. (2021). Assessing the impact of COVID-19 pandemic on emerging market economies' (EMEs) sovereign bond risk premium and fiscal solvency. *Eastern Economic Journal*, *47*, 519–545. https://doi.org/10.1057/s41302-021-00201-y

Boitan, I. A., & Marchewka-Bartkowiak, K. (2022). Climate change and the pricing of sovereign debt: Insights from European markets. *Research in International Business and Finance*, *62*, Article 101685. https://doi.org/10.1016/j.ribaf.2022.101685

Cathcart, L., Gotthelf, N. M., Uhl, M., & Shi, Y. (2020). News sentiment and sovereign credit risk. *European Financial Management*, *25*(2), 261–287. https://doi.org/10.1111/eufm.12219

Cecchetti, S. (2020). *An analysis of sovereign credit risk premia in the euro area: Are they explained by local or global factors?* (Bank of Italy Temi di Discussione Working Paper No. 1271). https://doi.org/10.2139/ssrn.3612941

Chen, K., Zhou, Y., & Dai, F. (2015, October). A LSTM-based method for stock returns prediction: A case study of China stock market. In *2015 IEEE International Conference on Big Data* (*Big Data*) (pp. 2823–2824). Santa Clara, CA, USA. IEEE. https://doi.org/10.1109/BigData.2015.7364089

Chen, Z., & Reitz, S. (2020). Dynamics of the European sovereign bonds and the identification of crisis periods. *Empirical Economics*, *58*, 2761–2781. https://doi.org/10.1007/s00181-019-01653-0

Ciżkowicz, P., Parosa, G., & Rzońca, A. (2022). Fiscal tensions and risk premium. *Empirica*, *49*(3), 833–896. https://doi.org/10.1007/s10663-022-09532-1

Comelli, F. (2012). Emerging market sovereign bond spreads: Estimation and back-testing. *Emerging Markets Review*, *13*(4), 598–625. https://doi.org/10.1016/j.ememar.2012.09.002

Corradin, S., & Schwaab, B. (2023). Euro area sovereign bond risk premia before and during the Covid-19 pandemic. *European Economic Review*, *153*, Article 104402. https://doi.org/10.1016/j.euroecorev.2023.104402

De Grauwe, P., & Ji, Y. (2012). Mispricing of sovereign risk and macroeconomic stability in the Eurozone. *Journal of Common Market Studies*, *50*(6), 866–880. https://doi.org/10.1111/j.1468-5965.2012.02287.x

De Spiegeleer, J., Madan, D. B., Reyners, S., & Schoutens, W. (2018). Machine learning for quantitative finance: Fast derivative pricing, hedging and fitting. *Quantitative Finance*, *18*(10), 1635–1643. https://doi.org/10.1080/14697688.2018.1495335

Della Corte, P., Jeanneret, A., & Patelli, E. D. (2023). A credit-based theory of the currency risk premium. *Journal of Financial Economics*, *149*(3), 473–496. https://doi.org/10.1016/j.jfineco.2023.06.002

Di Cesare, A., Grande, G., Manna, M., & Taboga, M. (2012). *Recent estimates of sovereign risk premia for euro-area countries* (Bank of Italy Occasional Paper No. 128). https://doi.org/10.2139/ssrn.2159218

Doshi, H., Jacobs, K., & Zurita, V. (2017). Economic and financial determinants of credit risk premiums in the sovereign CDS market. *The Review of Asset Pricing Studies*, *7*(1), 43–80. https://doi.org/10.1093/rapstu/rax009

Dougherty, J., Kohavi, R., & Sahami, M. (1995). Supervised and unsupervised discretization of continuous features. In A. Prieditis & S. Russell, (Eds.), *Machine learning proceedings 1995* (pp. 194–202). Morgan Kaufmann. https://doi.org/10.1016/B978-1-55860-377-6.50032-3

Erdem, O., & Varli, Y. (2014). Understanding the sovereign credit ratings of emerging markets. *Emerging Markets Review*, *20*, 42–57. https://doi.org/10.1016/j.ememar.2014.05.004

Fayek, A. R. (2020). Fuzzy logic and fuzzy hybrid techniques for construction engineering and management. *Journal of Construction Engineering and Management*, *146*(7), Article 04020064. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001854

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, *270*(2), 654–669. https://doi.org/10.1016/j.ejor.2017.11.054

Fontana, A., & Langedijk, S. (2019). *The bank-sovereign loop and financial stability in the Euro area* (JRC Working Papers in Economics and Finance No. 2019/10). Publications Office of the European Union.

Ghoddusi, H., Creamer, G. G., & Rafizadeh, N. (2019). Machine learning in energy economics and finance: A review. *Energy Economics*, *81*, 709–727. https://doi.org/10.1016/j.eneco.2019.05.006

Gilchrist, S., Wei, B., Yue, V. Z., & Zakrajšek, E. (2022). Sovereign risk and financial risk. *Journal of International Economics*, *136*, Article 103603. https://doi.org/10.1016/j.jinteco.2022.103603

Gumus, I. (2011). Exchange rate policy and sovereign spreads in emerging market economies. *Review of International Economics*, *19*(4), 649–663. https://doi.org/10.1111/j.1467-9396.2011.00972.x

Hafezi, R., Shahrabi, J., & Hadavandi, E. (2015). A bat-neural network multi-agent system (BNNMAS) for stock price prediction: Case study of DAX stock price. *Applied Soft Computing*, *29*, 196–210. https://doi.org/10.1016/j.asoc.2014.12.028

Hamrouni, C., & Chaoui, S. (2022). 5G smart mobility management based fuzzy logic controller unit. *Computers*, *Materials* & *Continua*, *71*(3), 4941–4953. https://doi.org/10.32604/cmc.2022.023732

Ho, T. K. (1998). The random subspace method for constructing decision forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *20*(8), 832–844. https://doi.org/10.1109/34.709601

Hofmann, B., Shim, I., & Shin, H. S. (2020). Bond risk premia and the exchange rate. *Journal of Money*, *Credit and Banking*, *52*(S2), 497–520. https://doi.org/10.1111/jmcb.12760

Huang, C. W., & Narayanan, S. S. (2017, July). Deep convolutional recurrent neural network with attention mechanism for robust speech emotion recognition. In *2017 IEEE International Conference on Multimedia and Expo* (*ICME*) (pp. 583–588). Hong Kong, China. IEEE. https://doi.org/10.1109/ICME.2017.8019296

Iara, A., & Wolff, G. (2014). Rules and risk in the Euro area. *European Journal of Political Economy*, *34*, 222–236. https://doi.org/10.1016/j.ejpoleco.2014.02.002

Kadiric, S. (2022). The determinants of sovereign risk premiums in the UK and the European government bond market: The impact of Brexit. *International Economics and Economic Policy*, *19*(2), 267–298. https://doi.org/10.1007/s10368-022-00535-8

Keller, J. M., Gray, M. R., & Givens, J. A. (1985). A fuzzy K-nearest neighbor algorithm. *IEEE Transactions on Systems*, *Man*, *and Cybernetics*, *15*(4), 580–585. https://doi.org/10.1109/TSMC.1985.6313426

Konopczak, K., & Konopczak, M., (2017). Impact of International capital flows on emerging markets' sovereign risk premium – demand vs. vulnerability effect. *Finance Research Letters*, *23*(C), 239–245. https://doi.org/10.1016/j.frl.2017.07.010

Lee, J., Kim, S., & Park, Y. J. (2017a). Investor sentiment and credit default swap spreads during the global financial crisis. *Journal of Futures Markets*, *37*(7), 660–688. https://doi.org/10.1002/fut.21828

Lee, Y. C., Chung, P. H., & Shyu, J. Z. (2017b). Performance evaluation of medical device manufacturers using a hybrid fuzzy MCDM. *Journal of Scientific and Industrial Research*, *76*(1), 28–31.

Linciano, N., Giordano, L., & Soccorso, P. (2013). Sovereign risk premia in the Euro Area and the role of contagion. *Journal of Financial Management*, *Markets and Institutions*, *1*(1), 85–114.

Ma, M., & Mao, Z. (2019, June). Deep recurrent convolutional neural network for remaining useful life prediction. In *Proceedings of the 2019 IEEE International Conference on Prognostics and Health Management* (*ICPHM*) (pp. 1–4). San Francisco. https://doi.org/10.1109/ICPHM.2019.8819440

Malliaropulos, D., & Migiakis, P. (2018). The re-pricing of sovereign risks following the Global Financial Crisis. *Journal of Empirical Finance*, *49*, 39–56. https://doi.org/10.1016/j.jempfin.2018.09.003

Maltritz, D., & Molchanov, A. (2013). Analyzing determinants of bond yield spreads with Bayesian Model Averaging. *Journal of Banking and Finance*, *37*(12), 5275–5284. https://doi.org/10.1016/j.jbankfin.2013.07.007

Marshall, M. G., & Elzinga-Marshall, G. (2017). *Global report 2017: Conflict*, *governance*, *and state fragility*. Center for Systemic Peace.

Martinez, L. B., Terceño, A., & Teruel, M. (2013). Sovereign bond spreads determinants in Latin American countries: Before and during the XXI financial crisis. *Emerging Markets Review*, *17*, 60–75. https://doi.org/10.1016/j.ememar.2013.08.004

Mpapalida, J., & Malikane, C. (2019). The determinants of sovereign risk premium in African countries. *Journal of Risk and Financial Management*, *12*(1), Article 29. https://doi.org/10.3390/jrfm12010029

Nauck, D., & Kruse, R. (1997). New learning strategies for NEFCLASS. In *Proceedings Seventh International Fuzzy Systems Association World Congress IFSA´97*, (vol. IV, pp. 50–55). Academia Prague.

Nauck, D., Klawonn F., & Kruse, R. (1997). *Foundations of neuro-fuzzy systems*. Wiley.

Norouzi, M., Collins, M. D., Johnson, M., Fleet, D. J., & Kohli, P. (2015). Efficient non-greedy optimization of decision trees. In *Advances in Neural Information Processing Systems 28* (*NIPS 2015*). The MIT Press.

Orlov, V. (2019) Solvency risk premia and the carry trades. *Journal of International Financial Markets, Institutions and Money*, *60*, 50–67. https://doi.org/10.1016/j.intfin.2018.12.001

Özmen, M. U. (2019). Economic complexity and sovereign risk premia. *Economics Bulletin*, *39*(3), 1714–1726.

Palić, P., Šimović, P. P., & Vizek, M. (2017). The determinants of country risk premium volatility: Evidence from a panel VAR model. *Croatian Economic Survey*, *19*(1), 37–66. https://doi.org/10.15179/ces.19.1.2

Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock market index using fusion of machine learning techniques. *Expert System with Applications*, *42*(4), 2162–2172. https://doi.org/10.1016/j.eswa.2014.10.031

Prashanth, K. D., Parthiban, P., & Dhanalakshmi, R. (2018). Evaluation and ranking of criteria affecting the supplier's performance of a heavy industry by fuzzy AHP method. *Journal of Scientific and Industrial Research*, *77*(5), 268–270.

Quinlan, J. R. (1993). *C4.5: Programs for machine learning*. Morgan Kaufmann Publishers Inc.

Rawal, B., & Agarwal, R. (2019). Improving accuracy of classification based on C4.5 decision tree algorithm using big data analytics. In *Advances in intelligent systems and computing: Vol. 711. Computational intelligence in data mining* (pp. 203–211). Springer. https://doi.org/10.1007/978-981-10-8055-5_19

Rundo, F., Trenta, F., di Stallo, A. L., & Battiato, S. (2019). Machine learning for quantitative finance applications: A survey. *Applied Sciences*, *9*(24), Article 5574. https://doi.org/10.3390/app9245574

Salas, M. B., Alaminos, D., Fernández-Gámez, M. A., & Callejón, A. M. (2020). Forecasting foreign exchange reserves using Bayesian model averaging-Naïve Bayes. *The Singapore Economic Review*, 1–22. https://doi.org/10.1142/S021759082048001X

Saltelli, A. (2002). Making best use of model evaluations to compute sensitivity indices. *Computer Physics Communications*, *145*(2), 280–297. https://doi.org/10.1016/S0010-4655(02)00280-1

Sánchez-Roger, M., Oliver-Alfonso, M. D., & Sanchís-Pedregosa, C. (2019). Fuzzy logic and its uses in finance: A systematic review exploring its potential to deal with banking crises. *Mathematics*, *7*(11), Article 1091. https://doi.org/10.3390/math7111091

Seoane, H. D. (2019). Time-varying volatility, default, and the sovereign risk premium. *International Economic Review*, *60*(1), 283–301. https://doi.org/10.1111/iere.12353

Siklos, P. (2011). Emerging market yield spreads: Domestic, external determinants, and volatility spillovers. *Global Finance Journal*, *22*(2), 83–100. https://doi.org/10.1016/j.gfj.2011.10.001

Sirignano, J., & Cont, R. (2019). Universal features of price formation in financial markets: Perspectives from deep learning. *Quantitative Finance*, *19*(9), 1449–1459. https://doi.org/10.1080/14697688.2019.1622295

Stolbov, M. (2017). Determinants of sovereign credit risk: The case of Russia. *Post-Communist Economies*, *29*(1), 51–70. https://doi.org/10.1080/14631377.2016.1237045

Thornton, J., & Vasilakis, C. (2017). The impact of fiscal rules on sovereign risk premia: International evidence. *Finance Research Letters*, *20*, 63–67. https://doi.org/10.1016/j.frl.2016.09.008

Tkalec, M., Vizek, M., & Verbic, M. (2014). Balance sheet effects and original sinners' risk premiums. *Economic Systems*, *38*(4), 597–613. https://doi.org/10.1016/j.ecosys.2014.05.005

Tsamardinos, I., Greasidou, E., & Borboudakis, G. (2018). Bootstrapping the out-of-sample predictions for efficient and accurate cross-validation. *Machine Learning*, *107*(12), 1895–1922. https://doi.org/10.1007/s10994-018-5714-4

Yang, Y., Garcia-Morillo, I., & Hospedales, T. M. (2018, July). Deep neural decision trees. In *Proceedings of the 2018 ICML Workshop on Human Interpretability in Machine Learning* (*WHI 2018*). Stockholm, Sweden. https://doi.org/10.48550/arXiv.1806.06988

Wang, S., Chen, X., Tong, C., & Zhao, Z. (2017). Matching synchrosqueezing wavelet transform and application to aeroengine vibration monitoring. *IEEE Transactions on Instrumentation and Measurement*, *66*(2), 360–372. https://doi.org/10.1109/TIM.2016.2613359

Zenios, S. A., Consiglio, A., Athanasopoulou, M., Moshammer, E., Gavilan A, & Erce, A. (2021). Risk management for sustainable sovereign debt financing. *Operations Research*, *69*(3), 755–773. https://doi.org/10.1287/opre.2020.2055

APPENDIX

Appendix A. Sample of developed countries

Australia	Greece	Norway
Austria	Iceland	Portugal
Belgium	Ireland	Spain
Canada	Italy	Sweden
Denmark	Japan	Switzerland
Finland	Luxembourg	United Kingdom
France	Netherlands	United States
Germany	New Zealand	

Appendix B. Sample of emerging countries

Chile	Korea, Rep.	Slovenia
Czech Republic	Poland	South Africa
Hungary	Russian Federation	Turkey
Israel	Slovak Republic	

Appendix C. Global sample

Australia	Hungary	Portugal
Austria	Ireland	Russian Federation
Belgium	Israel	Slovak Republic
Canada	Italy	Slovenia
Chile	Korea, Rep.	South Africa
Czech Republic	Japan	Spain
Denmark	Mexico	Sweden
Finland	Luxembourg	Switzerland
France	Netherlands	Turkey
Germany	New Zealand	United Kingdom
Greece	Norway	United States
Iceland	Poland	