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Is the energy transition impacting the Eurozone sovereign credit risk? Evidence from Machine Learning ☆

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ABSTRACT

We investigate whether the energy transition can influence sovereign credit risk in the Eurozone using Machine Learning methods. Specifically, we employ Random Forest and Neural Network regression models to analyse the relationship between 10-year government bond spreads and the quantity of renewable energy produced in 10 countries that adopted the Euro as their currency since its inception. To this purpose, we tune the model hyperparameters so that the models forecasts the one-step-ahead bond spreads as accurately as possible, and we use SHapley Additive exPlanation (SHAP) values to examine the relevance of the models features. The results show that Random Forests and Neural Networks display good forecasting performances. As for the energy transition, it shows a moderate influence on the sovereign credit spreads, both when renewable energy is normalized by GDP and when it is considered in terms of rate of change. In addition, higher variations are associated with larger SHAP values, showing that rapid shifts in energy policies may influence the credit spreads. Overall, as may be expected, the energy transition does not play a major role as a driver of the sovereign credit risk; however, it is intersting that it displays some in infuence nonetheless.

1. Introduction

European governments are undertaking unprecedented policy initiatives and public investment to support the transition toward a low-carbon economy. Flagship initiatives such as the European Green Deal exemplify this commitment, establishing legally binding targets to reduce greenhouse gas emissions by 55% by 2030 and to achieve climate neutrality by 2050 (see Andersson et al., 2025)). Achieving these objectives will require substantial financial resources: according to European Commission estimates, meeting the climate targets will necessitate hundreds of billions of Euros in green investment per year, amounting to a sizeable share of the European Union's overall economic output (see again Andersson et al., 2025). Such large-scale climate-oriented expenditures and regulatory interventions may impact sovereign bond markets through multiple channels. On the one hand, financing the green transition could place pressure on public finances, as increased government spending and debt issuance may lead investors to demand higher sovereign risk premia. On the other hand, a credible and well-designed shift toward clean energy may enhance long-term fiscal sustainability and macroeconomic resilience. In this perspective, countries that proactively pursue ambitious climate policies could be perceived as safer investments; consistent with this view, sovereigns regarded as climate laggards have been shown to face higher borrowing costs relative to their greener peers. Alternatively, investors may fail to incorporate climate-transition risks into sovereign pricing in the short run (see, for instance, Collender et al., 2023, and related references in Section 2), leaving sovereign credit risk largely unaffected. Against this backdrop, the overall contribution of the energy transition to Eurozone sovereign credit risk remains an open empirical question with substantial policy relevance. This paper aims to address this question by examining the relationship between the low-carbon transition and sovereign risk across Eurozone countries.

To shed light on this relationship, a recent strand of the literature has begun to examine the effects of climate change and transition risks on government bond markets (see, for instance, Bowman et al., 2022, and related references in Section 2). This body of work suggests that the link between climate action and sovereign borrowing costs is heterogeneous across countries. In particular, countries that are slow or reluctant to transition toward a low-carbon economy may face higher financing costs, whereas countries that are more strongly committed to decarbonisation may benefit from relatively lower government bond

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yields. Empirical evidence is broadly consistent with this heterogeneity. For instance, Collender et al. (2023) show that countries characterised by lower CO_2 emissions and a greater reliance on renewable energy tend to exhibit narrower sovereign bond spreads, while a heavy dependence on fossil fuels is associated with wider spreads. These findings point to the emergence of a climate-related risk premium in sovereign debt markets, whereby countries that are more climate-vulnerable or carbon-intensive face higher costs of capital. This mechanism has, in turn, raised concerns about a potential climate-sovereign *shape doom loop*, in which climate vulnerability and fiscal stress may mutually reinforce one another (see, for instance, Zenios, 2024). At the same time, other contributions caution that climate-related factors may not yet be fully incorporated into sovereign risk pricing, particularly in the short run (see, for instance, again Collender et al., 2023, and related references in Section 2). Overall, the policy question of how the green transition affects sovereign debt markets – through channels such as pressures on public finances, investors' perceptions of the credibility of climate policies, or the presence of unpriced climate risks – remains highly relevant and far from conclusively resolved.

Concurrently, in recent years there has also been a remarkable increase in the use of Machine Learning (ML)[1] methods to economic and financial research relevant to the present study (see the relevant references in Section 2). While these ML models and related applications have shown the usefulness of ML methods in investigating economic and financial phenomena, to the best of our knowledge, no studies have attempted to apply ML techniques to analyse the contribution of the energy transition to sovereign credit risk. However, the complexity and acknowledged nonlinearity of climate-related risks (see, for instance, Battiston and Monasterolo, 2020, and related references in Section 2) make ML models particularly well suited for this purpose.

In this paper, we contribute to the literature by analysing the relationship between Eurozone sovereign bond spreads and the energy transition using ML methodologies. Specifically, we develop predictive models based on Random Forests (RFs)[2] and Neural Networks (NNs)[3] using monthly data on 10-year government bond spreads for a panel of Eurozone countries. The choice of both the country sample and the time horizon is guided by considerations of economic coherence and data suitability. Focusing on Euro area member states allows us to examine sovereign credit risk within a monetary union characterised by a common currency, a single monetary policy, and integrated financial markets, thereby helping to limit heterogeneity related to exchange-rate regimes and monetary-policy autonomy. This institutional homogeneity contributes to the comparability of sovereign bond spreads across countries and facilitates the interpretation of cross-country differences primarily in terms of fiscal conditions and energy-transition dynamics, rather than monetary factors. The sample period from January 2012 to December 2023 is chosen to cover a phase during which climate and energy-transition policies gained increasing prominence in Europe, following the sovereign debt crisis and encompassing major climate-policy milestones, including the Paris Agreement and the European Green Deal. At the same time, this period provides sufficiently long time series to support the application of ML methods, which generally benefit from larger samples. The analysis is intended to shed light on whether incorporating energy-transition factors into sovereign risk dynamics can enhance our understanding of the evolution of sovereign bond spreads. To this end, we train and tune the ML models and subsequently employ them to forecast one-step-ahead changes in sovereign bond spreads as accurately as possible, where one step corresponds to a monthly horizon. Furthermore, we employ SHapley Additive exPlanations (SHAP)[4] values to assess the relevance of individual features within the ML models and, in particular, to evaluate whether energy-transition factors play a role in shaping the predictions. This approach is closely related to recent efforts aimed at extracting economic insights from the well-known black-box nature of ML models (see, for instance, Beckmann et al., 2023) and helps to provide insights into the channels through which the green transition may be affecting sovereign risk. Importantly, our contribution goes beyond the standard yet non-trivial claim that flexible ML models can accommodate nonlinearities in a generic sense. Rather, by combining ML prediction with SHAP-based interpretation, we show that the effect of renewable-energy variables is state-dependent: it is weak around ordinary monthly fluctuations, but becomes more pronounced in tail episodes characterised by unusually large changes in renewable-energy production. Hence, the added value of the ML approach lies in its ability to uncover asymmetric and tail-amplified predictive patterns that are averaged out by standard linear panel specifications. More broadly, these ML methods allow us to examine whether – and, if so, through which channels – the shift towards a low-carbon economy is influencing the Eurozone sovereign debt market, while avoiding some of the restrictive assumptions of traditional parametric approaches, most notably the linearity.

In summary, our research questions can be formulated as follows:

- Can ML models be exploited to effectively analyse the relationship between the low-carbon energy transition and sovereign credit risk in the Eurozone?
- Does the energy transition have a measurable contribution on Eurozone sovereign credit risk?

To answer these questions, rather than relying on conventional macroeconomic data, which are typically available at low frequency, we use monthly financial data to proxy various aspects of the economy (see, for details, Section 4). This approach allows us to focus on recent years and to obtain a sufficiently large sample for the application of ML models.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature; Sections 3 and 4 introduce the methodology and the data employed in this study, respectively; Section 5 presents the results of the empirical investigation; and Section 6 concludes.

2. Literature review

In this section, we review selected strands of recent literature that frame our study, namely: the traditional macro-financial determinants of sovereign credit risk; the emerging evidence on climate change and the low-carbon energy transition as factors influencing sovereign risk; and the application of machine learning techniques in economic and financial risk modeling. We emphasise that the objective of this review is not to be exhaustive, but rather to provide a set of recent and relevant references.

With regard to the first strand, a substantial body of literature has established a strong link between sovereign bond spreads and

[1] Broadly speaking, the term "machine learning" refers to a large and heterogeneous family of approaches designed to identify complex features and/or relationships in high-dimensional spaces with limited human intervention in model specification (see, for details, López de Prado, 2020).

[2] RFs are ensemble learning methods that aggregate the outputs of multiple weak learners – typically decision trees (DTs) – to produce a more robust overall output. DTs, in turn, are learning approaches designed to address complex classification and regression tasks.

[3] A NN can be viewed as a computational model inspired by the architecture and functioning of biological neural systems in higher-order living organisms. It comprises interconnected computational units that receive data, transform them through internal processing, and generate outputs, typically aimed at identifying complex patterns or relationships embedded in the data.

[4] SHapley Additive exPlanations is a game-theoretic approach for explaining ML models by fairly attributing each feature's contribution to the model's outputs.

both country-specific fundamentals and global market conditions. Traditional determinants include fiscal and macroeconomic indicators – such as public debt, budget deficits, economic growth, and external balances – as well as channels of international contagion and financial sector interconnectedness. For instance, Galariotis et al. (2016) employ a panel VAR framework to show that shocks to one country's sovereign CDS spread can spill over to others, while Georgoutsos and Moratis (2017) document significant bank-to-sovereign contagion effects within the Eurozone. Moreover, heightened uncertainty in economic and regulatory policies is associated with higher sovereign risk premia. In particular, Wisniewski and Lambe (2015) find that increases in policy uncertainty are linked to widening CDS spreads. Overall, this literature underscores that sovereign borrowing costs are highly sensitive to domestic fundamentals as well as to broader investor sentiment. Moreover, recent network- and entropy-based analyses show that sovereign risk dynamics reflect the interaction between country-specific fundamentals, global shocks, and financial network structures. For instance, using a fractional transfer entropy framework, Akgüller et al. (2025b) demonstrate that global equity markets quickly incorporate new information while remaining anchored to persistent linkages, whereas Balcıet al. (2022b) show that financial network geometry shifts significantly during crises, reconfiguring interdependencies and amplifying shock transmission. Overall, these findings indicate that sovereign credit risk is embedded in an interconnected system where traditional macro-financial determinants interact with network effects and global risk sentiment, especially under stress.

With respect to the evidence that climate change and the low-carbon energy transition constitute determinants of sovereign risk, a growing body of empirical research points to the existence of a climate risk premium in sovereign debt markets, whereby countries that are more exposed or vulnerable to climate-related hazards face higher financing costs. For example, Beirne et al. (2021) find that greater vulnerability to climate change significantly increases sovereign borrowing costs, while Cevik and Jalles (2022) show that climate-related shocks adversely affect sovereign bond valuations. In European markets in particular, investors appear to demand compensation for climate risk: Boitan and Marchewka-Bartkowiak (2022) document that various climate risk metrics are priced into sovereign bond yields and spreads. A closely related strand of the literature examines the impact of the low-carbon energy transition on sovereign debt markets. Transition risks – arising from policy, economic, regulatory, and technological shifts associated with the move toward a greener economy – are increasingly being reflected in sovereign credit spreads. Specifically, countries lagging in decarbonization tend to face higher borrowing costs, whereas those leading in renewable energy adoption appear to benefit from relatively lower financing costs. For instance, Collender et al. (2023) find that lower CO_2 emissions and greater reliance on renewable energy are associated with narrower government bond spreads, while heavy dependence on fossil fuel resources correlates with wider spreads. Similarly, Chaudhry et al. (2020) show that higher per capita CO_2 emissions significantly increase country risk in the G7 economies. Importantly, these transition-related effects are not uniform across countries and may be amplified by climate policy uncertainty. In this regard, Jia et al. (2024) report that higher climate policy uncertainty is associated with greater volatility in sovereign bond returns, suggesting that inconsistent or ambiguous climate actions exacerbate sovereign risk. Moreover, recent sectoral and network-based studies indicate that the low-carbon transition can affect risk fundamentals through interconnected production and financial channels. In particular, Akgüller et al. (2025a) show that the electricity and energy sectors act as central hubs in shock transmission, implying that decarbonisation policies or transition-related disturbances—such as shifts in energy production or carbon pricing—can propagate across industries and markets. This channel suggests that climate-transition risks may indirectly influence aggregate macro-financial conditions and sovereign credit risk beyond their direct fiscal and environmental implications.

Finally, with regard to the third strand, the application of machine learning (ML) methodologies to economic and financial research relevant to the present study has expanded markedly in recent years. For example, in the field of climate finance, Nguyen et al. (2021) employ several ML algorithms, including RFs and NNs, to predict firms' greenhouse gas emissions. In the area of credit risk analysis, Sigrist and Leuenberger (2023) develop a tree-boosted algorithm for credit scoring prediction. In macro-finance, Goulet Coulombe (2024) introduce a macroeconomic system representation based on RFs, while Heger et al. (2024) show that ML methodologies – including Bayesian Regularised NNs, Bayesian Additive DTs, and RFs – provide accurate forecasts of changes in U.S. and Eurozone covered and corporate bond credit spreads. In the context of sovereign debt, Belly et al. (2023) demonstrate that ML algorithms are able to capture the dynamics of Euro area sovereign risk more effectively than standard approaches. Finally, Balcıet al. (2024) employ a convolutional NN to quantify economic news sentiment, showing that sentiment fluctuations are associated with changes in market complexity, a proxy for financial instability. Complementarily, Balcıet al. (2022a) go beyond ML techniques by proposing a network-induced soft set model to capture stock market dynamics, offering an alternative approach to the evaluation of complex risk factors. Furtherome, despite the inherently black-box nature of many machine learning methods, explainability techniques, most notably SHAP values (see Beckmann et al., 2023), are increasingly employed to assess the relevance of economic and/or financial variables in ML-based models.

3. Methodology

We employ two different methodologies to forecast sovereign bond spreads, namely, Random Forests and Neural Networks. Furthermore, we rely on SHAP values to analyse the importance of the model features in the prediction.

It may be useful to clarify the rationale underlying the choice of ML methodologies adopted in this study. RFs and NNs are selected as they represent two complementary and widely used classes of nonlinear models that differ markedly in their structure, learning mechanisms, and sources of flexibility. Employing these two distinct approaches allows us to assess the robustness of the results across fundamentally different ML paradigms.

The choice of RFs and NNs is motivated not solely by their ability to capture nonlinear relationships, but also by the specific nature of our empirical problem, namely a forecasting-and-attribution analysis conducted on a panel characterised by persistence in sovereign spreads, multiple correlated financial controls, and potentially weak, state-dependent transmission channels linking the energy transition to sovereign risk. In such settings, the relevant benchmark is not the statistical significance of the structural coefficients, but rather the ability of the model as a whole to generate reliable out-of-sample predictions while preserving an economically meaningful interpretation of the underlying signal. This perspective is well established in the recent ML literature, which emphasises that supervised learning methods such as RFs and NNs are particularly well suited to contexts characterised by model uncertainty, high-dimensional control variables, and potentially complex interactions, especially when researchers lack sufficient theoretical grounds to impose restrictive functional-form assumptions ex ante (see Mullainathan and Spiess, 2017; Athey and Imbens, 2019).

RFs are theoretically appealing in this context because they estimate the conditional expectation through adaptive partitioning and averaging. As such, they are particularly well suited to capturing threshold effects, regime dependence, and local interactions without requiring the researcher to specify them ex ante. This feature is especially relevant in the present setting, where the contribution of renewable energy dynamics to sovereign spreads is unlikely to be homogeneous across countries and market conditions: the same variation in renewable energy production may be priced differently when market volatility is elevated, credit conditions deteriorate, or sovereign spreads are already under stress. Moreover, RF-based methods have been shown to perform particularly well in approximately sparse environments, that is, in settings where only a subset of the available predictors carries substantial predictive information within a given region of the state space, while the remaining covariates are only weakly informative or intermittently relevant (see, for instance, Athey and Imbens, 2019). Relative to linear panel specifications, RFs can therefore uncover heterogeneous and state-contingent patterns that would otherwise be averaged out. At the same time, relative to more traditional nonparametric methods, they are less sensitive to the presence of weakly informative covariates, since the splitting mechanism adaptively selects the predictors that are locally most informative.

NNs are complementary to RFs. Whereas tree-based ensembles are particularly effective at capturing local thresholds and irregular interactions, NNs provide a flexible approximation of smooth multivariate functions generated through layered combinations of the input variables. This feature is especially relevant in our setting, where the energy transition may influence sovereign risk through several potentially offsetting channels. There are no theoretical grounds to expect these channels to enter the determination of sovereign spreads in either an additive or a globally linear manner. NNs are therefore theoretically well suited to this context, as they can represent smooth yet highly complex combinations of domestic and global financial variables. This justification is not merely heuristic: the theoretical literature demonstrates that even relatively simple NNs possess universal approximation properties (see, for instance, Hornik et al., 1989), while more recent contributions establish formal results concerning the estimation properties of modern NN architectures employed in empirical applications (see, for instance, Farrell et al., 2021).

The joint use of RFs and NNs also serves a broader methodological purpose. Recent contributions to the literature emphasise that no general theoretical result implies that one class of models should systematically dominate the other across all supervised learning problems. Accordingly, comparing two complementary algorithms characterised by different inductive biases is more informative than relying exclusively on a single flexible specification (see Athey and Imbens, 2019). In our setting, this comparative strategy is particularly valuable because the available sample is moderate in size and the economic objective does not constitute a purely algorithmic benchmarking comparison, but rather the extraction of an economically interpretable signal regarding the extent to which the energy transition contributes to sovereign spread dynamics. For this reason, we focus on two well-established methods that have already proven effective in closely related macro-financial and credit-risk applications, including sovereign-risk forecasting (see, for instance, Belly et al., 2023). We then tune them using validation schemes explicitly designed for grouped and time-ordered data, so that model complexity is managed in a manner that respects both the panel structure and the temporal dependence of the sample. In this sense, our methodology is theoretically appropriate not simply because it allows for nonlinearities, but because it matches the forecasting nature of the research question, the heterogeneous transmission channels suggested by economic theory, and the dependence structure of the data.

In summary, both models are well established in the recent economic and financial forecasting literature and have been shown to perform competitively relative to alternative algorithms in applications involving macro-financial time series and credit risk. Given the relatively limited cross-sectional dimension of the panel and the emphasis placed on interpretability through SHAP values, extending the analysis to additional ML methodologies is unlikely to yield qualitatively different economic insights, while potentially complicating both model comparison and the interpretation of the results.

In the following, we describe both techniques and then use SHAP values to interpret their predictions.

3.1. Random forests

The Random Forest (RF) algorithm (Breiman, 2001) is a Decision Tree (DT) based method that combines multiple DTs into a single model to achieve greater performance. Decision trees are developed for both classification and regression problems. A regression DT, i.e., the type of DT we are interested in here, obtains predictions of the response variable, y, by dividing the data into branches and by taking the average value of the observations in each branch. To partition the data, the regression DT builds (hyper-)rectangles R_j, with $j = 1, \dots, J$, in order to minimise the residual sum of squares:

$$\sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2, \tag{1}$$

where y_i is the ith observation, and $\hat{y}_{R_j}$ is the mean response for the observations within the (hyper-)rectangle R_j.

The RF algorithm creates B bootstrapped samples from the original data, selects p predictors randomly from the full set of M predictors, and fits a DT, $\hat{f}^b(X)$, for each sample. Finally, it aggregates the trees' responses by averaging their predictions:

$$\hat{f}_{avg} = \frac{1}{B} \sum_{b=1}^{B} \hat{f}^b(X). \tag{2}$$

In this way, the RF model reduces the dependence of all trees on a single strong variable and achieves predictions that are less correlated with each other.

3.2. Neural networks

Neural networks (NNs) are a nonlinear regression technique that tries to mimic the functioning of the human brain. In the NNs terminology, the set of M predictors and the response variables are called input and output layers, respectively. The units in the input layers are fed into K hidden units in the hidden layer,[5] transformed by a nonlinear activation function, and then fed into the output layer (Bishop, 1995). The one-hidden-layer NN model with a single response variable can thus be written as:

$$\hat{y} = \beta_0 + \sum_{k=1}^{K} \beta_k A_k, \tag{3}$$

where β_0 is the bias of the hidden layer to the response variable, β_k, with $k = 1, \dots, K$, is the kth weight of the hidden units to the response variable, and A_k is the output of the kth hidden unit, expressed as:

$$A_k = A_k(X_1, \dots, X_m, \dots, X_M) = g(w_{k,0} + \sum_{m=1}^{M} w_{k,m} X_m), \tag{4}$$

where X_m, with $m = 1, \dots, M$, is the mth predictor, $g(\cdot)$ is a nonlinear activation function, $w_{k,0}$ is the bias of the input layer to the kth hidden unit, and $w_{k,m}$ is the weight from the mth input unit to the kth hidden unit. An activation function that is commonly used in regression applications is the Rectified Linear Unit ($ReLU$):

$$g(z) = max(0, z). \tag{5}$$

To obtain estimates of the unknown parameters, a NN minimises the residual sum of squares through *back-propagation*, in which the biases and the weights are updated iteratively, calculating the gradient of the error function with respect to the weights and the biases, respectively.

[5] In this example, we consider a NN with a single hidden layer and a single response variable, but it is possible to extend the methodology to include multiple hidden layers and multiple response variables.

3.3. SHAP

In this paper, we rely on the Shapley Additive exPlanations approach (Lundberg and Lee, 2017), or SHAP, to assess which variables are most relevant for the prediction of sovereign risk. SHAP is a game theory-based approach that measures the marginal contribution of a variable to the prediction when it is added to the model. The expected marginal contribution of the generic ith feature is given by:

$$SHAP_i = \sum_{S\subseteq\{1,\dots,p\}\{i\}} \frac{|S|!(p-|S|-1)!}{p!}[v(S\cup\{i\})-v(S)] \qquad i=1,\dots,p \quad (6)$$

where $SHAP_i$ is the contribution of the ith variable, with $i = 1,\dots,p$, S is the coalition,[6] and $v(S)$ is the value of the coalition S computed as the expected value of the model prediction when only the input features in S are considered. Notice that the larger $SHAP_i$, the larger the contribution of the ith feature to the overall prediction.

It is important to emphasise that, while SHAP-based explanations do not provide causal estimates in a structural or policy-evaluation sense, they should not be conflated with simple correlation measures. Unlike pairwise correlations or linear regression coefficients, SHAP values are computed conditional on the full multivariate structure learnt by the model and quantify each feature's marginal contribution to the prediction across all possible coalitions of covariates. Accordingly, SHAP values capture how a variable contributes to the model's output in the presence of all other predictors, including non-linear interactions and higher-order dependencies. In this sense, SHAP provides conditional, model-consistent attribution rather than an unconditional statistical association. Therefore, the SHAP analysis can be regarded as a valid and informative tool for assessing the economic relevance of the energy transition within a predictive sovereign risk framework.

A further implication is that global SHAP summaries should be interpreted in conjunction with local explanation tools, such as dependence plots (see, for instance, Lundberg et al., 2020). A feature may display a relatively small mean absolute SHAP value and yet remain economically informative if its contribution is concentrated in a limited subset of observations, for instance in tail states or during episodes of abrupt adjustment. In such cases, the feature does not operate as a uniform average driver of the dependent variable. Rather, it acts as a state-contingent factor whose relevance becomes visible only in specific regions of the predictor space.

4. Data

Before collecting the data, we specify the conceptual model that relates a Eurozone country's sovereign risk to its energy transition. To this end, we survey the literature on sovereign credit risk to identify the main factors that may describe such a relationship. Our conceptual model is:

$$Sovereign_{i,t} = f(Transition_{i,t-1}, Sovereign_{i,t-1}, Domestic_{i,t-1}, Foreign_{t-1}) \quad (7)$$

where the sovereign risk for country i at time t, $Sovereign_{i,t}$, is a function of the country's energy transition, $Transition_{i,t-1}$, previously observed sovereign risk, $Sovereign_{i,t-1}$, domestic controls, $Domestic_{i,t-1}$, and foreign controls, $Foreign_{t-1}$. The inclusion of foreign controls is motivated by empirical evidence that shows that changes in the global stock and bond markets can explain variations in a country's sovereign credit risk (see Blommestein et al., 2016).

In this paper, we focus on the EU member states that adopted the Euro as their currency since its introduction[7] in 2002, that is, Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. To proxy their energy transition, we collect monthly data on the production of renewable energy (in gigawatt hour, GWh) from the International Energy Agency (IEA), between January 2012 and December 2023, and compute the rate of change.[8] As for sovereign credit risk, we consider the monthly 10-year government bond spreads with respect to the German government 10-year bond yield, obtained from Bloomberg. The data on domestic and foreign controls, which we detail below, are also obtained from Bloomberg.

As domestic controls, we follow Blommestein et al. (2016) and employ domestic stock market returns and volatility (calculated with a GARCH(1,1) model) to proxy the economic state and volatility of the country's economy. Analogously, we use EuroStoxx 50 and SP500 returns to represent the EU and US economies, and the EuroStoxx 50 Volatility Index and the VIX to measure their volatility (see Belly et al., 2023). Moreover, we consider the iTraxx Europe corporate CDS spread and the CDX North American Investment Grade as indicators for the European and American bond market developments (Wisniewski and Lambe, 2015; Georgoutsos and Moratis, 2017). Finally, following Galariotis et al. (2016), we include the rate of change of the Economic Sentiment Indicator (ESI), published monthly by the European Commission to monitor EU business and consumer confidence. Table 1 reports a summary of the variables.

In the end, our panel dataset is made up of 1440 country-month observations. In Table 2 we report the descriptive statistics for the model variables. The average Spread for the Eurozone countries considered is 1.48, with a standard deviation equal to 2.67, indicating that, in general, variation between countries is limited. As for the rate of change of the renewable energy produced (REP), it displays a mean equal to 0.27 and a standard deviation of 6.57. Notably, the Spread has a skewness equal to 5.30, hence, a few countries with extremely high spreads (e.g., Greece) stretch the right tail of the distribution; in addition, both Spread and REP have large kurtosis, meaning that the distribution is peaked around the mean, with most values close to it. The Jarque–Bera test rejects the normality of the distribution of all the variables considered at the 1% significance level.

Table 3 reports the correlation matrix of the model variables. The correlation between Spread and REP is 0.035, indicating that these two variables are weakly linearly related. However, there could still be non-linear effects not captured by the linear correlation. On the other hand, the Spread is highly correlated with the iTraxx (0.355) and the CDX (0.293), suggesting that European sovereign spreads partly reflect broader credit market conditions. The REP variable is lowly correlated with all the other independent variables, while other covariates, such as the VStoxx and the VIX are largely correlated (0.909). This indicates that caution is needed when fitting the linear model, as potential multicollinearity among the variables could inflate standard errors.

5. Results

In this section, we report the empirical results and discuss their implications, adopting a framework that links technical findings to broader economic insights. We begin by establishing the baseline statistical properties and linear associations between renewable energy

[6] In the context of SHAP, a coalition refers to a subset of input features that work together to contribute to the prediction of the considered model. To compute the SHAP value associated with the ith input feature, all possible coalitions that include this feature are taken into account.

[7] We exclude Luxembourg from the analysis due to the lack of data. Moreover, other studies focused on the Eurozone do not consider this country (e.g., Galariotis et al., 2016).

[8] Since we notice that the time series related to the production of renewable energy follow a seasonal pattern, we remove the seasonal component with the STL decomposition method (Cleveland et al., 1990), so that seasonal variations do not influence the predictions. Not only several authors suggest that this is beneficial (see Martinez et al., 2018, for a list), but we also do observe a better forecasting performance.

Table 1
List of the model variables (January 2012–December 2023, monthly frequency).

Name	Type	Description
Spread	Sovereign	Difference between 10-year domestic and German bond yields
REP	Transition	Rate of change of country's renewable energy production in GWh
Stock	Domestic	Domestic stock market return
Vol	Domestic	Domestic stock market volatility, obtained with a GARCH(1,1)
EuroStoxx	Foreign	EuroStoxx 50 return
SP500	Foreign	SP500 return
VStoxx	Foreign	EuroStoxx 50 Volatility Index
VIX	Foreign	CBOE Volatility Index
iTraxx	Foreign	iTraxx Europe 10-year CDS spread
CDX	Foreign	CDX North American Investment Grade 10-year CDS spread
ESI	Foreign	Rate of change of the European Sentiment Indicator

Table 2
Descriptive statistics of the model variables.

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Jarque–Bera
Spread	1.48	2.67	−0.01	30.79	5.30	43.02	102,820.00***
REP	0.27	6.57	−26.89	35.41	0.47	6.73	884.04***
Stock	0.46	5.49	−33.12	25.77	−0.67	6.85	995.56***
Vol	1.21	0.50	0.57	5.86	3.00	17.26	14,355.00***
EuroStoxx	0.46	4.73	−17.79	16.60	−0.26	4.15	94.78***
VStoxx	21.08	6.21	11.99	48.59	1.24	5.26	672.11***
iTraxx	76.79	27.29	43.65	179.40	1.40	4.74	651.41***
SP500	1.04	3.92	−13.09	12.25	−0.52	4.50	200.25***
VIX	15.64	6.27	8.06	48.80	1.95	8.39	2655.80***
CDX	71.08	16.15	45.27	123.56	0.81	3.22	160.23***
ESI	0.02	2.09	−20.93	7.37	−6.71	72.47	298,260.00***

* : $p < 0.1$, ** : $p < 0.05$, and *** : $p < 0.01$.

Table 3
Correlation analysis of the model variables.

	1	2	3	4	5	6	7	8	9	10	11
Spread	1										
REP	0.035	1									
Stock	−0.048	−0.010	1								
Vol	0.419	−0.011	−0.194	1							
EuroStoxx	−0.004	−0.006	0.802	−0.141	1						
VStoxx	0.070	0.007	−0.402	0.561	−0.457	1					
iTraxx	0.355	0.025	−0.145	0.253	−0.145	0.365	1				
SP500	−0.003	−0.008	0.563	−0.091	0.709	−0.382	−0.160	1			
VIX	−0.095	−0.008	−0.362	0.438	−0.398	0.828	0.130	−0.405	1		
CDX	0.293	0.007	−0.247	0.418	−0.258	0.537	0.909	−0.284	0.327	1	
ESI	−0.017	0.061	0.012	−0.330	0.046	−0.177	−0.125	−0.141	−0.217	−0.183	1

indicators and sovereign bond spreads (Sections 5.1 and 5.2). We then assess the robustness of these initial results through a set of supplementary checks and a panel Granger causality analysis (Sections 5.3 and 5.4). Subsequently, we employ the aforementioned ML methodologies to forecast sovereign risk with a high degree of accuracy (Section 5.5), and we interpret the ML models' outputs using SHAP values, which allow us to quantify the contribution of renewable energy factors to sovereign credit risk (Section 5.6). Overall, this stepwise strategy provides a coherent narrative that highlights the implications of our findings for sovereign risk assessment, energy transition policies, and financial stability.

It is noteworthy that Sections 5.1 to 5.4 play a preparatory and benchmarking role, as they establish the statistical properties of the data, examine linear dynamic relationships, and assess the extent to which standard empirical tools are able to detect a link between the energy transition and sovereign credit risk. These analyses provide a necessary reference framework against which the subsequent ML–based results can be interpreted. Building on this foundation, Sections 5.5 and 5.6 move beyond linear specifications and exploit flexible, nonlinear modeling approaches to forecast sovereign bond spreads and to evaluate the economic relevance of renewable energy variables through SHAP-based interpretability techniques.[9]

This structured progression enables a comparison between evidence obtained from standard empirical tools and ML–based results, thereby clarifying both the limitations of conventional methods and the additional insights that can be gained from more general and flexible modeling frameworks.

5.1. Unit root tests

Before estimating the linear model relating sovereign risk to the energy transition, we perform several unit root tests to check the stationarity of the variables and determine whether cointegration techniques should be employed. For domestic variables, such as Spread, REP, and Stock, we perform several panel unit root tests. For foreign

[9] It should be noted that the econometric and panel-data analyses reported in Sections 5.1 to 5.4 were conducted using *Stata*®, while the ML-based analyses reported in Sections 5.5 and 5.6 were implemented in *Python*™.

Table 4
Panel unit root tests for domestic variables. H_0: All panels contain unit roots. H_a: Some panels are stationary. Lag length selection is based on Modified Akaike Information Criterion (MAIC). Bandwidth is selected using the Newey–West procedure with a Bartlett kernel. Levin, Lin & Chu test assumes a common unit root process, all the other tests assume an individual unit root process.

Variable	Levin, Lin & Chu t-Stat	Im, Pesaran & Shin W-Stat	ADF - Fisher Chi-square	PP - Fisher Chi-square
Spread	−6.812***	−5.413***	91.257***	128.171***
REP	−67.963***	−60.714***	894.194***	419.823***
Stock	−30.579***	−25.246***	504.987***	840.986***
Vol	−10.018***	−7.141***	102.923***	271.160***

* : $p < 0.1$, ** : $p < 0.05$, and *** : $p < 0.01$.

Table 5
Unit root tests for foreign variables. For the ADF and PP tests H_0: The series has a unit root; H_a: The series is stationary. For the KPSS test H_0: The series is stationary; H_a: The series has a unit root. Lag length selection is based on Akaike Information Criterion (AIC). Bandwidth is selected using the Newey–West procedure with a Bartlett kernel.

Variable	ADF	PP	KPSS
EuroStoxx	−12.671***	−13.698***	0.058
SP500	−10.623***	−12.827***	0.084
VStoxx	−3.960***	−5.142***	0.102
VIX	−3.938***	−4.739***	0.658**
iTraxx	−3.022**	−2.876*	0.508**
CDX	−3.838***	−3.631***	0.431*
ESI	−8.725***	−8.404***	0.071

* : $p < 0.1$, ** : $p < 0.05$, and *** : $p < 0.01$.

variables, such as EuroStoxx and SP500, we apply simple time series unit root tests, since these variables do not vary across countries.

Table 4 shows the results of the panel unit root tests applied to the domestic variables. All employed tests (Levin, Lin, and Chu; Im, Pesaran, and Shin; ADF Fisher Chi-square; and PP Fisher Chi-square) reject the null hypothesis that all panels contain a unit root at the 1% significance level. Therefore, we conclude that the domestic variables are stationary and do not require differencing. Consequently, cointegration techniques are not required. This does not imply that a relationship between sovereign risk and the energy transition is absent; rather, it means that cointegration methods are not appropriate for investigating this relationship, since I(0) variables cannot share a common trend.

In Table 5 we report the results of the unit root tests applied to foreign variables. The tests consistently indicate that EuroStoxx, SP500, VStoxx, and ESI are stationary (note that in the KPSS test, the null hypothesis is stationarity). For VIX, iTraxx, and CDX, results are mixed: the ADF and Phillips–Perron tests suggest that VIX and CDX are stationary at the 1% significance level, and iTraxx at the 10% level, whereas the KPSS test rejects stationarity for VIX and iTraxx at 5% and CDX at 10%. Since two out of three tests indicate that these series are stationary at least at the 10% level, we do not difference them in the first stage. As a robustness check, however, we will later consider their potential non-stationarity and estimate models using differenced variables.

5.2. Regression analysis

To examine the relationship between sovereign credit risk and the energy transition, we first employ linear regression methods before progressing to more advanced machine learning techniques. In detail, based on the key conceptual model in Eq. (7), we estimate the following fixed-effects regression:

$$
\begin{aligned}
Spread_{i,t} = \beta_0 &+ \beta_1 Spread_{i,t-1} + \beta_2 REP_{i,t-1} + \beta_3 Stock_{i,t-1} \\
&+ \beta_4 Vol_{i,t-1} + \beta_5 EuroStoxx_{t-1} \\
&+ \beta_6 VStoxx_{t-1} + \beta_7 iTraxx_{t-1} + \beta_8 SP500_{t-1} \\
&+ \beta_9 VIX_{t-1} + \beta_{10} CDX_{t-1} \\
&+ \beta_{11} ESI_{t-1} + \gamma_i + \epsilon_{i,t}
\end{aligned}
\tag{8}
$$

where γ_i represents country fixed effects for country i and $\epsilon_{i,t}$ is the error term. Robust standard errors are clustered at the country level. In addition to the fixed effects model, we also estimate a random effects model and apply the Hausman test to determine which is the best method of estimation.

Note from Eq. (8) that the lagged dependent variable is included among the covariates. To estimate such a dynamic panel model, one would typically employ an estimator designed for this purpose, such as the Arellano–Bond GMM estimator (Arellano and Bond, 1991). However, these GMM estimators rely on instruments constructed from lagged values of the dependent variable. When T is large, the number of instruments grows rapidly, which can lead to a nearly singular instrument matrix and make estimation infeasible. Consequently, in panels with large T, standard Arellano–Bond GMM may not be appropriate. Given that our panel has a relatively small number of countries ($N = 10$) and a long time dimension ($T = 144$), the bias associated with including a lagged dependent variable in a fixed-effects model is expected to be very small (Nickell, 1981, reports that such bias is approximately $\mathcal{O}(1/T)$). Therefore, we rely on standard fixed-effects estimation to analyse the dynamic relationship, as the bias is negligible and more complex GMM methods, such as Arellano–Bond, are unnecessary in this context.

Table 6 displays the results of the regression estimates. In Column 1, we report the results of the fixed effects regression model with country fixed effects. The coefficient on the lagged Spread is positive and significant at the 1% level, showing persistence over time. Conversely, the coefficient on the REP variable is not statistically different from 0, indicating that no significant linear relationship emerges between sovereign credit risk and the energy transition. These results hold when we add year-month fixed effects to the model (Column 2), and when we employ country random effects[10] (Column 3). In this regard, the Hausman test indicates that the random effect model is inconsistent ($\chi^2 = 41.90$, $p = 0.000$), which supports the use of the fixed-effects specification. Moreover, the joint significance of the fixed effects is confirmed by the F-test ($F = 4.88$, $p = 0.000$).

To test for the presence of potential multicollinearity, we compute the variance inflation factor (VIF). The results indicate that the VIF values are above the recommended threshold of 10 (Hair et al., 1995), meaning that the estimated standard errors are likely inflated. In the next subsection, we will address this matter.

5.3. Robustness checks

We conduct a range of robustness checks. The results are reported in Table 7. First, in Columns 1 and 2, we take the first differences of the variables that raised concerns about potential non-stationarity, namely iTraxx, VIX, and CDX. Second, in Columns 3 and 4, we exclude highly correlated variables (Vol, VStoxx, and CDX) to reduce multicollinearity and bring the VIF values below the recommended threshold of 10. Finally, in Columns 5 and 6, we estimate model (8) without the lagged spread among the covariates.

The results are consistent with those reported in the previous subsection. The Spread is primarily explained by its lagged value, both when we take first differences of potentially non-stationary variables and when we remove variables with high VIF. In both cases, the coefficient on REP is not statistically significant, whether we use only country fixed effects or include year-month fixed effects. The only exception occurs when the lagged spread is excluded from the covariates, in

[10] We also attempt to estimate a specification including both country and year-month random effects yet the estimation fails to converge.

Table 6
Regression estimates. Standard errors are clustered at the country level and are reported in parentheses.

	Spread		
Variable	(1)	(2)	(3)
Lagged Spread	0.8773***	0.8824***	0.9106***
	(0.0156)	(0.0116)	(0.0154)
REP	0.4308	0.3431	0.4165
	(0.3447)	(0.2594)	(0.3420)
Stock	0.0114	0.0094	0.0136
	(0.0109)	(0.0100)	(0.0124)
Vol	0.0386	−0.0256	0.1144
	(0.0543)	(0.0684)	(0.0839)
EuroStoxx	−0.0203	−0.0324	−0.0241
	(0.0213)	(0.0265)	(0.0238)
VStoxx	0.0037	−0.0352	−0.0031
	(0.0048)	(0.0349)	(0.0026)
iTraxx	0.0021**	−0.0264	0.0017*
	(0.0009)	(0.0371)	(0.0009)
SP500	0.0071	0.0040	0.0075
	(0.0102)	(0.0099)	(0.0108)
VIX	−0.0081	−0.0332	−0.0028
	(0.0083)	(0.0392)	(0.0046)
CDX	−0.0015	0.0391	−0.0026
	(0.0009)	(0.0564)	(0.0017)
ESI	0.7411	−0.3283	1.2218
	(0.6786)	(3.6047)	(0.8983)
Constant	0.0803**	0.4330**	0.1108**
	(0.0263)	(0.1814)	(0.0530)
Obs.	1420	1420	1420
Adj. R square	0.950	0.958	0.950
Country Fixed effects	Yes	Yes	No
Year-month Fixed effects	No	Yes	No
Country Random effects	No	No	Yes

* : $p < 0.1$, ** : $p < 0.05$, and *** : $p < 0.01$.

which case the REP coefficient is significant at the 10% level; however, it loses significance once year-month fixed effects are included. Overall, these findings confirm the absence of a linear relationship between sovereign risk and the energy transition. To investigate potential nonlinear relationships, more advanced methods are required, motivating our use of machine learning techniques.

5.4. Granger causality test

To inspect the dynamic and linear relationship between sovereign risk and the energy transition, we employ the Dumitrescu–Hurlin test (Dumitrescu and Hurlin, 2012), an extension of the Granger causality test (Granger, 1969) for panel data. In the Dumitrescu–Hurlin test, the null hypothesis is that X does not Granger-cause Y for any cross-section in the panel. In other words, the test verifies whether there is evidence of a uniform causal effect of X on Y, and vice versa, across all panel units.

Table 8 reports the results of the test. The null hypothesis that Spread does not cause REP cannot be rejected ($W = 11.88$, $\bar{Z} = -0.21$, $p = 0.83$), hence there is no evidence of a uniform causal effect of Spread on REP. Similarly, it appears that REP does not homogeneously cause Spread ($W = 11.64$, $\bar{Z} = -0.35$, $p = 0.73$), which is consistent with the evidence we have found in the panel regression analysis, that is, there is no linear relationship between sovereign risk and the energy transition in the Eurozone. The Dumitrescu–Hurlin test suggests that there is no dynamic relationship between the two variables. The results of the test provide additional evidence about the absence of a relationship between Spread and REP detectable with linear methods, further justifying the usage of nonlinear ML models.

Taken together, the results reported in Sections 5.1 to 5.4 provide a useful benchmark for interpreting the ML evidence presented below. The absence of statistically significant linear relationships, together with the lack of evidence of homogeneous linear Granger-causal links between renewable energy production and sovereign bond spreads, indicates that potential effects of the energy transition are not easily captured by standard linear or homogeneous dynamic frameworks. This conclusion, however, does not rule out the possibility that renewable-energy variables may still contain predictive information within a more flexible nonlinear framework. For this reason, the linear and Granger-causality evidence should be viewed as a benchmark rather than as contradicting the ML results reported below.

From a comparative perspective, these findings help to frame the ML results in Sections 5.5 and 5.6. When ML models suggest a non-negligible contribution of renewable-energy variables to spread predictions, such contributions may be consistent with nonlinear, state-dependent, or asymmetric patterns that are difficult to detect using conventional techniques. In this sense, the ML evidence should be interpreted as documenting a moderate, state-dependent, and predictive contribution of renewable-energy variables, rather than as establishing a structural causal effect.

5.5. Forecasting sovereign credit risk

The linear regression model failed to detect the possible relationship between sovereign risk and the energy transition. Thus, we advocate for the usage of techniques that can move past the traditional assumption of linearity. To analyse if the energy transition risk is priced in the Eurozone sovereign bond market, we need to build ML models that successfully forecast sovereign bond spreads. Hence, we design a cross-validation procedure to verify the goodness of the model architectures. Subsequently, we can apply model-agnostic techniques to inspect the importance of the model features in the prediction.

First, we divide the dataset into two subsets: an in-sample set, which includes observations up to December 2020, and an out-of-sample set, containing the remaining observations up to December 2023. The in-sample set is used for training the models, while the out-of-sample set is used for one-step-ahead forecasting of country spreads. To tune the main hyperparameters of the Random Forest and the Neural Network, we apply a randomised grid search. The model performance is assessed, both in-sample and out-of-sample, using standard metrics: mean absolute error, MAE, root mean squared error, $RMSE$, mean absolute percentage error, $MAPE$, and the coefficient of determination, R^2. The use of R^2 as a measure of goodness of fit for ML-based approaches has been – and continues to be – subject to criticism due to its partial unsuitability for nonlinear models, such as RFs and NNs. Nevertheless, the R^2 remains widely used in the specialised literature on ML applications, even for comparative purposes when the goodness of fit of different (nonlinear) models is assessed (see, for instance, Sapra, 2014). In this contribution, we also adopt R^2 for this purpose.

Second, to validate the selected hyperparameters, we apply a cross-validation technique designed for panel data. As our data are structured in groups, this approach ensures that the integrity of the groups is maintained when the data are split into training and testing sets.[11] Specifically, we create a sequence of K randomised partitions where, for each split, a subset of the countries is held out as the testing sample. Each split is performed independently, hence some countries may appear in multiple testing samples, while others are likely to never appear if K is low. Thus, we set $K = 50$, with a proportion of training/testing countries equal to 70/30. The fine-tuning is performed using a randomised grid search.

Finally, we apply an additional cross-validation where the data are split in training and testing samples, based on time. Note that temporal dependencies are explicitly accounted for in both the cross-validation

[11] Note that we apply this technique because standard K-fold validation method is designed for i.i.d. sample, but in our application we are dealing with a panel, so we need to shuffle groups of observations, rather than single observations.

Table 7
Robustness checks results. Standard errors are clustered at the country level and are reported in parentheses.

	Spread					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Spread	0.8912***	0.8824***	0.8808***	0.8811***		
	(0.0149)	(0.0116)	(0.0109)	(0.0091)		
REP	0.4130	0.3431	0.4333	0.3425	0.9462*	0.8989
	(0.3238)	(0.2594)	(0.3462)	(0.2587)	(0.4955)	(0.7007)
Stock	0.0119	0.0094	0.0112	0.0096	−0.0096	−0.0128**
	(0.0120)	(0.0100)	(0.0102)	(0.0096)	(0.0066)	(0.0051)
Vol	0.0463	−0.0256			1.3655	2.5281**
	(0.0812)	(0.0684)			(0.8018)	(1.0991)
EuroStoxx	−0.0177	−0.0539	−0.021	−0.1223	−0.0017	0.0787*
	(0.0169)	(0.0417)	(0.0215)	(0.0865)	(0.0104)	(0.0382)
VStoxx	−0.0022	−0.0655			0.0278	0.0888
	(0.0042)	(0.0614)			(0.0300)	(0.0647)
iTraxx			0.0016**	−0.0078	0.0460**	0.1951**
			(0.0007)	(0.0129)	(0.0148)	(0.0812)
SP500	0.0037	0.1611	0.0086	0.2736	−0.0188**	−0.0837*
	(0.0077)	(0.2266)	(0.0113)	(0.1910)	(0.0067)	(0.0381)
VIX			−0.0045	0.2131	−0.1055	0.3276**
			(0.0033)	(0.1621)	(0.0648)	(0.1373)
CDX					−0.0384**	−0.3304**
					(0.0129)	(0.1415)
ESI	0.9667	0.4255	0.655	−0.6496*	0.0524	−0.3746*
	(0.8874)	(0.5827)	(0.4514)	(0.3499)	(0.0401)	(0.1862)
ΔiTraxx	0.0063	0.0058				
	(0.0074)	(0.0252)				
ΔVIX	0.0015	−0.0724				
	(0.0041)	(0.0922)				
ΔCDX	−0.0078	0.0658				
	(0.0079)	(0.0798)				
Constant	0.1088***	1.1555	0.0779**	−2.5321	0.0564	0.3487
	(0.0131)	(0.8936)	(0.0284)	(1.7646)	(0.6486)	(0.4897)
Obs.	1420	1420	1420	1420	1420	1420
Adj. R square	0.950	0.958	0.950	0.958	0.327	0.471
Country Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month Fixed effects	No	Yes	No	Yes	No	Yes

* : $p < 0.1$, ** : $p < 0.05$, and *** : $p < 0.01$.

Table 8
Dumitrescu–Hurlin test. Lag length selection is based on Akaike Information Criterion (AIC)

Null hypothesis	W-stat	$\bar{Z}$-stat	p-value
Spread does not homogeneously cause REP	11.8804	−0.2081	0.8352
REP does not homogeneously cause Spread	11.6448	−0.3480	0.7278

Table 9
Performance metrics of Random Forests and Neural Networks in the in-sample set (2012–2020m12) and the out-of-sample set (2021m1–2023). The best value for each metric is reported in bold.

	In sample				Out of sample			
	MAE	RMSE	MAPE	R^2	MAE	RMSE	MAPE	R^2
Random Forest	**0.076**	**0.257**	**0.085**	**0.991**	**0.070**	0.107	**0.106**	0.961
Neural Network	0.192	0.394	0.275	0.979	0.071	**0.102**	0.118	**0.965**

and fine-tuning. Specifically, to this end, we avoid shuffling the data during training. In such an approach, the testing sample starts from January 2021 and the testing set "rolls" forward with each split. The hyperparameters are optimised through a randomised grid search.

Both cross-validation methods yield hyperparameter values similar to those found in the first place. The final list of hyperparameter values is reported in Table A.1, Appendix A. In the following, we present the results of the models using the in-sample set consisting of observations up to December 2020 and the out-of-sample set covering the period January 2021 to December 2023.

In Table 9 we report the values of the performance metrics for the RF and NN models. Both of them perform very well,[12] displaying low MAE, $RMSE$, and $MAPE$, and a high R^2. The usage of a panel dataset is thus useful to cope with the limited amount of data available for a single country. Note that, in addition to ReLU, we assessed several other activation functions for the hidden nodes prior to cross-validation – namely, the linear, sigmoid, and hyperbolic tangent functions. However, based on the results from the error metrics, we decided to discard these functions due to the superior performance of ReLU.

Table 10 reports the values of the metrics calculated on every single country. Again, the results point out the good performance of RFs and NNs in forecasting the Spread. As one might expect, the higher $RMSE$ values are associated with riskier countries, such as Greece (RF: 0.227, NN: 0.219, both out-of-sample) or Italy (RF: 0.172, NN: 0.143, both out-of-sample). This is confirmed by the scatterplot in Fig. 1. In Appendix B, we graphically present the forecasts obtained for each country by the Random Forest and the Neural Networks, both for the in-sample and out-of-sample sets.

Lastly, Table 11 shows, for each metric, the ratio between its value achieved in the out-of-sample set by RFs (numerator) and by NNs (denominator). These ratios are calculated for each country. All computed values are around 1, indicating that RFs and NNs obtain similar forecasting results.

The reliable forecasting performance of both the RF and NN models carries significant policy-relevant implications. From an operational

[12] We also considered additional models where the energy transition is represented by the ratio of renewable energy production to GDP, obtaining slightly worse results in terms of performance metrics.

Table 10
Performance metrics of the Random Forest and Neural Network models in the in-sample period (2012–2020m12) and the out-of-sample period (2021m1–2023), calculated for each country. The best value for each country–metric combination is indicated in bold.

	In sample				Out of sample			
	MAE	RMSE	MAPE	R^2	MAE	RMSE	MAPE	R^2
Random Forest								
Austria	**0.020**	**0.027**	**0.077**	**0.973**	**0.047**	**0.059**	**0.119**	**0.898**
Belgium	**0.025**	**0.036**	**0.050**	**0.987**	**0.041**	**0.052**	**0.083**	**0.891**
Finland	**0.017**	**0.023**	**0.290**	**0.931**	**0.044**	0.059	**0.109**	0.889
France	**0.022**	**0.030**	**0.049**	**0.977**	0.048	0.063	0.098	0.661
Greece	**0.321**	**0.643**	**0.041**	**0.984**	**0.169**	0.227	0.109	0.806
Ireland	**0.057**	**0.132**	**0.053**	**0.995**	**0.055**	**0.069**	**0.119**	**0.471**
Italy	**0.070**	**0.101**	**0.035**	**0.986**	0.128	0.172	0.079	0.825
Netherlands	**0.016**	**0.022**	**0.096**	**0.961**	**0.035**	**0.044**	**0.150**	**0.782**
Portugal	**0.104**	**0.161**	**0.040**	**0.994**	0.067	0.096	0.086	0.713
Spain	**0.055**	**0.090**	**0.035**	**0.994**	0.068	0.087	0.078	0.769
Neural Network								
Austria	0.088	0.108	0.387	0.568	0.054	0.063	0.150	0.886
Belgium	0.078	0.096	0.204	0.912	0.051	0.058	0.113	0.861
Finland	0.075	0.090	0.857	−0.021	0.046	**0.056**	0.135	**0.901**
France	0.083	0.101	0.220	0.748	**0.041**	**0.048**	**0.094**	**0.802**
Greece	0.713	1.009	0.109	0.961	0.177	**0.219**	**0.108**	**0.821**
Ireland	0.174	0.405	0.184	0.955	0.058	0.071	0.135	0.434
Italy	0.205	0.284	0.105	0.890	**0.111**	**0.143**	**0.066**	**0.879**
Netherlands	0.067	0.080	0.455	0.466	0.044	0.054	0.235	0.677
Portugal	0.272	0.430	0.108	0.958	**0.063**	**0.091**	**0.080**	**0.742**
Spain	0.170	0.246	0.116	0.954	**0.060**	**0.076**	**0.067**	**0.823**

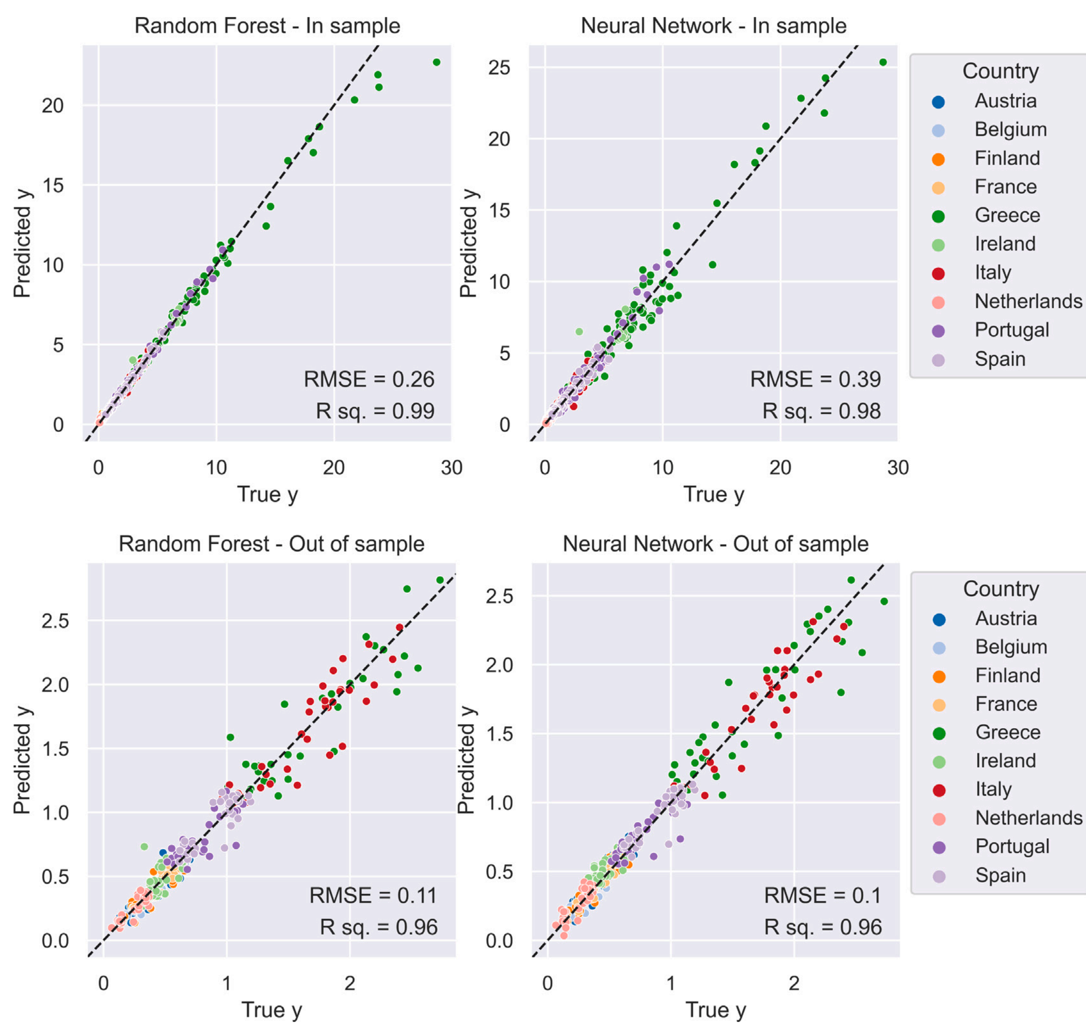

Fig. 1. Predicted vs. true 10-year sovereign bond spreads for the in-sample period (2012–2020m12) and the out-of-sample period (2021m1–2023).

Table 11
Ratios of out-of-sample performance metrics for Random Forests relative to Neural Networks (2021m1–2023). Each entry is the value of the metric for the Random Forest model divided by the corresponding value for the Neural Network model, by country.

Out of sample				
	MAE	RMSE	MAPE	R^2
Austria	0.870	0.937	0.793	1.014
Belgium	0.804	0.897	0.735	1.035
Finland	0.957	1.054	0.807	0.987
France	1.171	1.313	1.043	0.824
Greece	0.955	1.037	1.009	0.982
Ireland	0.948	0.972	0.881	1.085
Italy	1.153	1.203	1.197	0.939
Netherlands	0.795	0.815	0.638	1.155
Portugal	1.063	1.055	1.075	0.961
Spain	1.133	1.145	1.164	0.934

standpoint, the high level of predictive accuracy suggests that advanced ML approaches can be effectively employed as early-warning instruments for sovereign risk monitoring. Supervisory authorities, central banks, and fiscal policymakers could incorporate these tools into their surveillance frameworks to proactively identify and address emerging vulnerabilities in sovereign debt markets, thereby enhancing macro-financial stability. Moreover, the ability of the models to preserve satisfactory predictive performance when renewable energy variables are included indicates that climate transition–related factors can be systematically integrated into sovereign risk assessment without undermining forecasting reliability. This supports the case for embedding energy transition metrics into policy-oriented risk monitoring systems and underscores the value of non-linear modelling approaches as a complement to conventional sovereign risk assessment frameworks in an environment of increasing climate-related financial risks.

5.6. Assessing the contribution of the energy transition to sovereign risk

In this subsection, we employ SHAP values to assess the contribution of the energy transition to sovereign risk. Fig. 2 displays the mean SHAP value for the features in the RF and NN models. Both models rely heavily on lagged Spread to make the prediction, although in the NN the contributions of the other features is more balanced. In both cases, the contribution of the energy transition is minimal. In other words, it appears that the renewable energy factor contributes subtly to the overall prediction, suggesting that the energy transition is only slightly priced into the sovereign bond market.

This evidence should be interpreted with caution. SHAP values do not identify structural causal effects; rather, they measure the contribution of each variable to the model's prediction conditional on the full multivariate information set. Moreover, the mean absolute SHAP value is a global average across observations. Consequently, a variable may have modest average importance and yet still matter in specific states of the system. In our context, this implies that renewable-energy variables should not be interpreted as dominant drivers of sovereign spreads, but rather as secondary predictors whose contribution may become more visible in particular episodes.

Such findings are to be expected for at least three reasons. First of all, our analysis refers to the time period during which the EU member states listed above began to pay significant attention to the renewable energy produced, that is from January 2012 to December 2023. This increased attention was primarily driven by the Paris Agreement on climate change and the preceding consultations and negotiations. Therefore, it is understandable that, in such a relatively short period of time, the contribution of the energy transition to sovereign risk has only begun to be experienced. On the contrary, it would be surprising if, in such a short period, the energy transition had become a major driver of 10-year government bond spreads.

The second reason is based on the fact that, according to the literature on the factors affecting sovereign credit risk presented in the previous section, the energy transition is never considered among the major drivers. Therefore, our results are consistent with these findings. However, we note that, particularly in the case of the RF, the contribution of the energy transition is roughly comparable in magnitude to that of other well-established factors, such as the VIX and the CDX (see Fig. 2).

The final reason is that the energy transition may affect sovereign credit risk in two opposing ways. The first is that the shift towards a low-carbon economy generally has a positive effect on the country in terms of reputation, which, to some extent, improves the evaluation of its sovereign credit risk. The second is that the energy transition necessitates additional public spending, which has an obviously negative contribution to the sovereign credit risk assessment. Our study assesses the contribution of the net effect of these two opposing forces to sovereign credit risk, irrespective of their individual magnitudes.

For instance, a government that rapidly and aggressively expands renewable energy capacity may benefit from a reputational gain associated with climate leadership – potentially strengthening investor confidence and reducing perceived sovereign risk – while simultaneously giving rise to short-term fiscal concerns stemming from the scale of required public investment, which may exert upward pressure on sovereign spreads. Conversely, a country that lags behind in renewable energy adoption may avoid immediate green-related expenditures but could be perceived as less resilient to future energy shocks or forthcoming carbon regulations, a perception that may ultimately weigh on its creditworthiness. Our findings indicate that, over the past decade, these opposing channels have largely offset one another, resulting in the modest net effect of the energy transition on sovereign bond spreads observed in the data.

We continue our analysis by conducting a robustness check. To this end, we re-estimate the models without the lagged spread. The results are reported in Fig. 3. The contribution of the variable associated with the energy transition grows, yet remains moderate, especially, as shown below, in the NN model. These results are further confirmed when we employ the ratio of renewable energy production to GDP as the REP factor (see Appendix C). These robustness checks corroborate the hypothesis that the energy transition has a contribution to sovereign credit risk in the Eurozone, even if modest.

To obtain more precise insight into the type of nonlinearity uncovered by the ML models, we examine the SHAP dependence plots reported in Fig. 4. These plots indicate that the energy-transition effect is not merely nonlinear in a generic sense. Rather, it is *state-dependent* and concentrated in specific regions of the predictor space. In the RF model, the relationship between REP and its SHAP contribution is U-shaped, implying that relatively ordinary changes in renewable-energy production are associated with limited contributions to spread predictions, whereas unusually large changes are associated with larger contributions. In the NN model, the mapping is approximately monotone and piecewise linear, consistent with the ReLU architecture. Here too, however, the absolute contribution becomes materially larger in the tails. Thus, although the exact global functional form differs across the two ML architectures, an evident empirical regularity emerges: the contribution of the renewable-energy variable is small around normal fluctuations and becomes more relevant during unusually large transition-related changes.

This pattern provides an economic interpretation of the observed nonlinearity. The energy transition may affect sovereign spreads through offsetting channels. On the one hand, stronger renewable-energy dynamics may improve perceptions of climate-policy credibility, energy resilience, and long-run macro-fiscal sustainability. On the other hand, abrupt changes in the transition path may signal implementation risk, short-run fiscal pressure, adjustment costs, or policy uncertainty. When these channels broadly offset one another, the

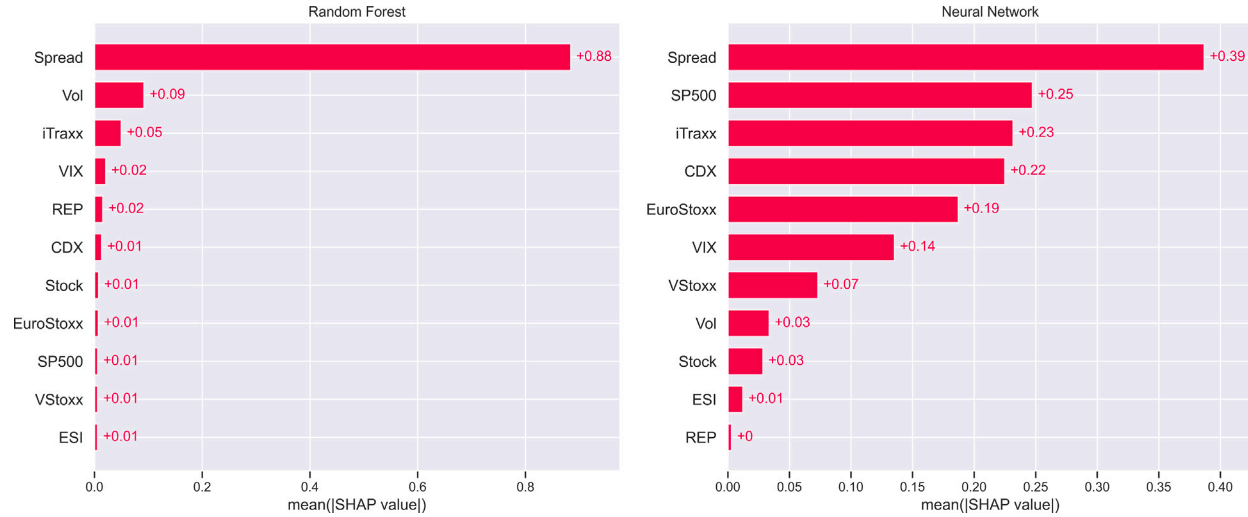

Fig. 2. Mean SHAP values for each feature in the Random Forest and Neural Network models.

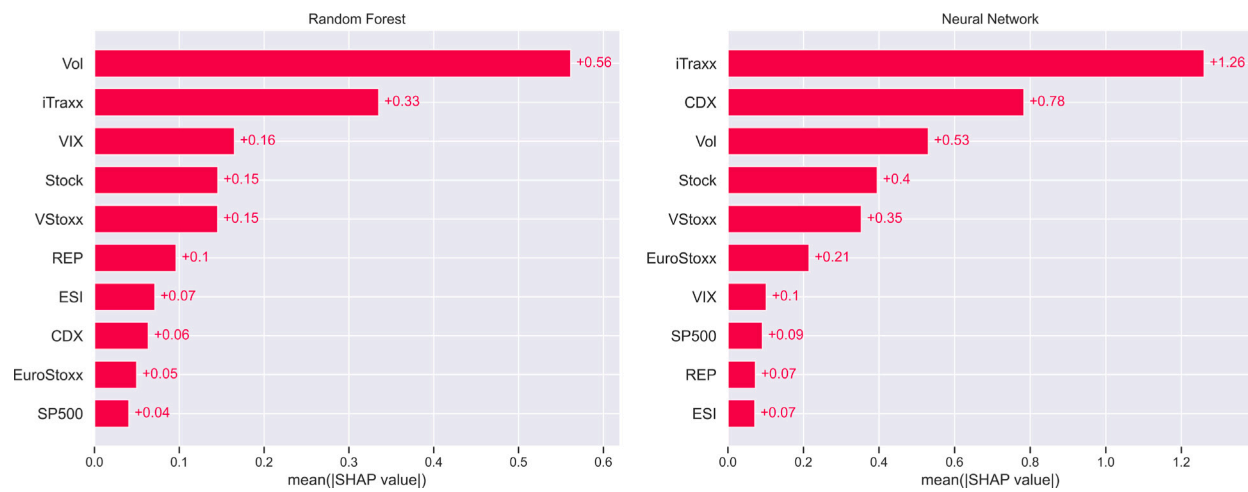

Fig. 3. Mean SHAP values for each feature in the Random Forest and Neural Network models, estimated without the lagged $Spread$.

average contribution of the renewable-energy variable remains limited. By contrast, in tail episodes characterised by unusually large changes in renewable-energy production, these offsetting forces may no longer balance in the same way, making the variable more informative for spread predictions.

This interpretation also clarifies why the mean SHAP value of REP is modest. A small mean absolute SHAP value indicates that the energy transition is not a first-order average driver of Eurozone sovereign spreads over the full sample. However, it does not imply that the variable is economically irrelevant. Rather, the evidence suggests that renewable-energy variables behave as a moderate, state-contingent determinant: they contain little information in ordinary times, but provide additional information during episodes of abrupt transition dynamics. This is consistent with the robustness exercise excluding the lagged spread, in which the relative contribution of REP increases, indicating that transition-related information is partly masked by the strong persistence of sovereign spreads.

Hence, the added value of the ML approach relative to the linear panel benchmark does not lie merely in functional-form flexibility per se. The linear model and the panel Granger-causality tests only assess average homogeneous relationships and return null evidence. By contrast, the ML-SHAP framework reveals that the effect of the energy transition is localised, asymmetric, and stronger in tail observations. In this sense, the energy transition does not emerge as a dominant average driver of sovereign spreads, but rather as a state-dependent factor that becomes relevant when transition dynamics are unusually pronounced.

In summary, the dependence plots suggest that the role of the renewable-energy variable is concentrated away from the center of its distribution. In other words, small and regular changes in renewable-energy production are associated with limited effects on the model output, whereas unusually large positive or negative changes are associated with larger absolute SHAP values. We interpret this pattern as evidence of a state-dependent and tail-sensitive relationship rather than as a pervasive average effect. From an economic viewpoint, such a pattern is consistent with offsetting channels: gradual transition dynamics may be largely absorbed by markets, while abrupt changes may be interpreted either as signals of fiscal pressure or as signals of stronger transition credibility and resilience.

Overall, these results confirm the moderate contribution that the energy transition has to sovereign debt in the Eurozone, although notable changes in the energy policy might be factored into the bond market. Indeed, it seems that investors do not place much weight on the energy transition when determining the sovereign risk premium within safe countries, such as those in the Eurozone. However, investors could be concerned about rapid changes in energy policies and react accordingly. The fact that the energy transition is not widely factored into the Eurozone sovereign debt market signals that policymakers have not yet succeeded in convincing investors of the urgency of the energy

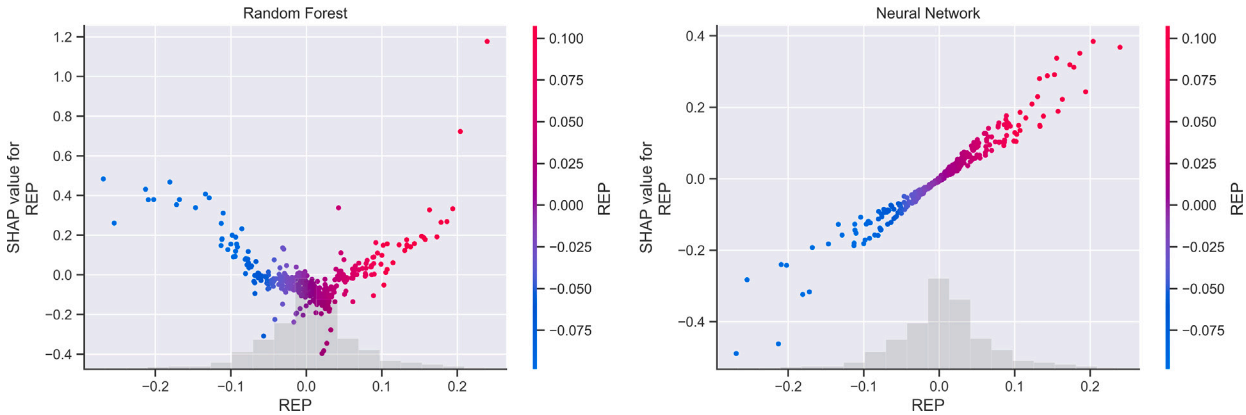

Fig. 4. SHAP dependence plots for key features in the Random Forest and Neural Network models. The vertical color bar to the right of each plot indicates the value of the feature, with warmer colors representing higher feature values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

transition. We argue that the results found should encourage European policymakers to make efforts in this regard.

In practical terms, this implies that traditional determinants of sovereign spreads – such as a country's pre-existing risk profile and global financial market volatility – continue to dominate bond pricing, while progress in renewable energy provides minor adjustments. In other words, during the sample period, bond investors did not substantially reprice sovereign credit risk on the basis of the "greenness" of a country's energy mix, although they began to incorporate such information to a limited extent. Importantly, the fact that the estimated contribution of the renewable energy factor is of a comparable order of magnitude to well-established risk indicators such as the VIX (a benchmark of market volatility) and the CDX (a corporate credit risk index) suggests that the energy transition has entered the informational set of financial markets. This nuanced finding is consistent with recent evidence documenting the emergence of a modest climate-related risk premium in sovereign debt markets, notwithstanding the continued predominance of conventional economic drivers.

6. Conclusions

This paper investigates the contribution of the energy transition to sovereign risk in the Eurozone, using Random Forests and Neural Networks. We show that these two models are useful for forecasting 10-year bond spreads, and that the usage of a panel dataset allows one to obtain good results for the prediction of single countries' spread. We inspect the contribution that an energy transition factor has to the predicted values, through SHAP analysis. It appears that the renewable energy produced is a minor predictor of sovereign bond spread, according especially to the SHAP values for the Neural Network model. Furthermore, we find that extreme values of the energy transition variable are associated to higher SHAP values, so the market might react to marked energy policy shifts, although it is unclear whether this relationship is U-shaped or linear.

From a policy perspective, our findings indicate that the energy transition underway in the Eurozone has, to date, not generated significant tensions in sovereign debt markets. This result is particularly salient in the context of recent European initiatives, all of which entail substantial public investment commitments. The evidence presented in this study suggests that financial markets have not systematically penalised countries for expanding renewable energy capacity, implying that ambitious climate policies can be pursued without precipitating an immediate deterioration in sovereign credit conditions.

At the same time, the moderate contribution of renewable energy–related variables identified by the ML models indicates that investors are becoming increasingly attentive to energy-sector developments, especially when changes are rapid or large in magnitude. In this regard, the energy transition appears to function as a minor risk factor whose relevance may increase as climate policies intensify and the scale of green investment expands. Recent dynamics in European sovereign and supranational green bond markets – characterised by consistently strong investor demand – are consistent with this interpretation and point to a gradual incorporation of climate-related considerations into sovereign risk assessments.

All these results support the view that the energy transition and financial stability are not inherently at odds. Rather, a gradual, well-communicated, and credible transition strategy is unlikely to unsettle sovereign bond markets and may, over the longer term, contribute to enhanced economic resilience. This underscores the importance for policymakers of ensuring consistency and transparency in climate-related fiscal and energy policies, particularly as the transition progresses and its macro-financial implications become more pronounced.

Viewed in this light, our evidence should be read as documenting a moderate, nonlinear, and state-dependent predictive association between renewable-energy dynamics and sovereign spreads, rather than a systematic causal effect of the energy transition on sovereign risk. Traditional determinants of sovereign spreads remain dominant throughout the sample, while renewable-energy variables contribute only marginally on average. However, the dependence-plot evidence suggests that this contribution becomes more visible when renewable-energy dynamics are unusually large, indicating that the pace and abruptness of the transition may matter more than its average level. We therefore interpret the energy transition as an emerging but still non-dominant component of the informational set used by investors in Eurozone sovereign debt markets.

Before concluding, it is appropriate to acknowledge some limitations of the present study. First, the energy transition is proxied by renewable energy production and its growth rate, which represent observable and policy-relevant indicators, but may capture only specific facets of the transition process. Broader economic, regulatory, and technological dimensions – such as carbon pricing arrangements, fossil-fuel reliance, or climate policy uncertainty – could also be relevant for sovereign risk and may operate through channels that are not explicitly considered in this framework. The adopted proxies are primarily motivated by data availability at a monthly frequency and the need for cross-country consistency within the Eurozone, and should therefore be viewed as providing a partial characterisation of transition dynamics. Second, the analysis is restricted to a relatively homogeneous set of advanced Eurozone economies over the period 2012–2023. While this institutional homogeneity facilitates comparability across countries, it may also limit the generalisability of the results. Consequently, the findings should be interpreted with caution and not automatically extended

Table A.1
Hyperparameter values for the random forest and the neural network.

Model	Hyperparameter	Item selected	Sample
RF	Number of trees	100	{100}
RF	Depth of the tree	Unlimited	{10, 15, 20, 25, Unlimited}
RF	Number of features at each split	7	{4, 5, 6, 7, 8, All}
NN	Number of hidden layers	1	{1, 2}
NN	Number of neurons	15	{10, 15, 20, 25}
NN	Activation function	*ReLU*	{Hyperbolic tangent, Linear, *ReLU*, Sigmoid}

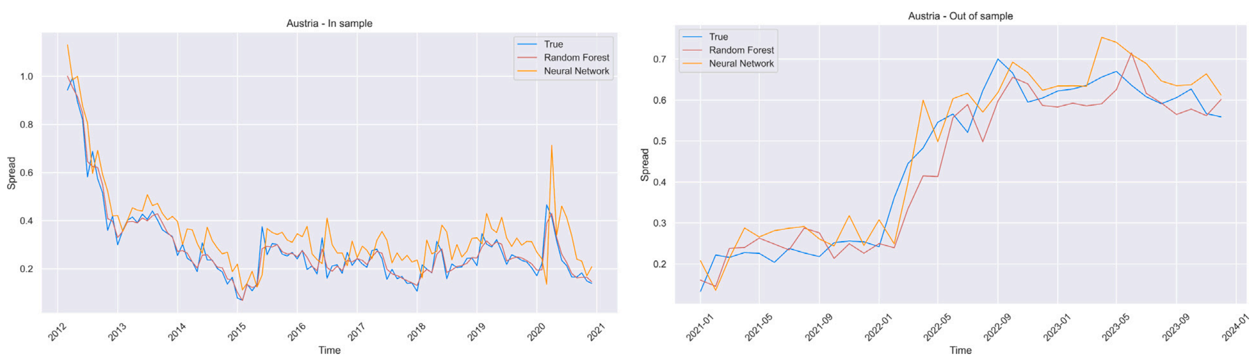

Fig. B.1. In-sample (left) and out-of-sample (right) time series for Austria.

to emerging economies or to countries with markedly different fiscal structures, energy systems, or exposure to climate-related risks. Finally, although SHAP values offer a model-consistent and economically interpretable assessment of variable importance, they are not designed to identify structural causal relationships. Accordingly, the estimated contribution of renewable energy variables should be understood as reflecting predictive associations rather than causal effects, particularly in the context of policy evaluation.

Overall, the results suggest that the energy-transition variables have, to date, played a moderate, state-dependent predictive role in Eurozone sovereign debt markets, a finding that is consistent with the early stage of the transition process over the sample period. Investors appear to have continued to place greater weight on traditional determinants of sovereign risk – such as underlying fiscal conditions and global financial volatility – while indicators related to the energy transition have so far played a secondary, albeit increasingly discernible, role. This pattern is indicative of a gradual incorporation of transition-related risks into sovereign bond pricing, rather than their outright neglect, and suggests that their relevance may strengthen as climate policies intensify and their macroeconomic and fiscal implications become more clearly defined. Importantly, the limited contribution of renewable energy variables should not be interpreted as evidence that energy transition dynamics are immaterial for sovereign risk assessment. On the contrary, the fact that their estimated relevance is already comparable in magnitude to that of well-established financial risk indicators points to the gradual emergence of the energy transition as a moderate, though increasingly discernible, component of the informational set used in Eurozone sovereign debt markets. From this perspective, the findings are best understood as providing descriptive evidence on the evolving informational set of investors, rather than normative guidance for policy design.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marco Corazza reports financial support was provided by European Union. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Hyperparameter values

See Table A.1.

Appendix B. Time series plots

In each of the figures above, the light blue line depicts the true values, the red line illustrates the RF forecasts, and the orange line indicates the NN forecasts (see Figs. B.1–B.10).

Appendix C. SHAP values robustness check

See Fig. C.1.

Data availability

The authors do not have permission to share data.

Replication_package.zip (Reference data) (Mendeley Data)

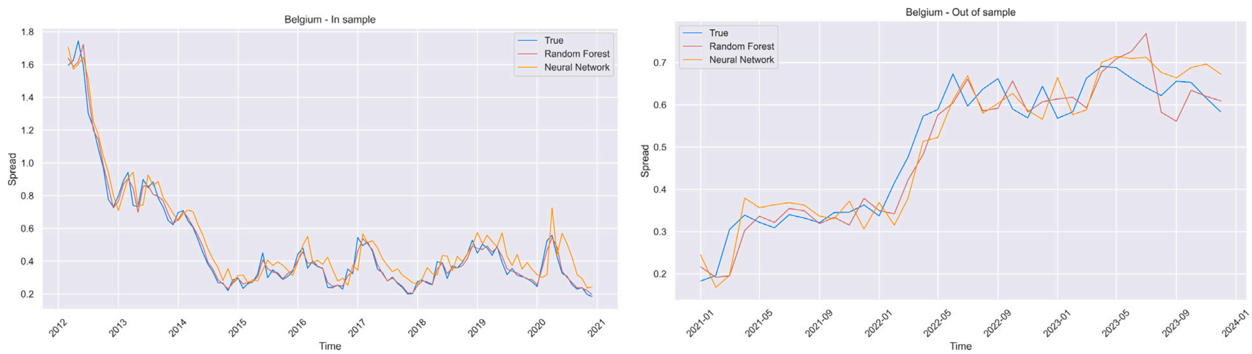

Fig. B.2. In-sample (left) and out-of-sample (right) time series for Belgium.

Fig. B.3. In-sample (left) and out-of-sample (right) time series for Finland.

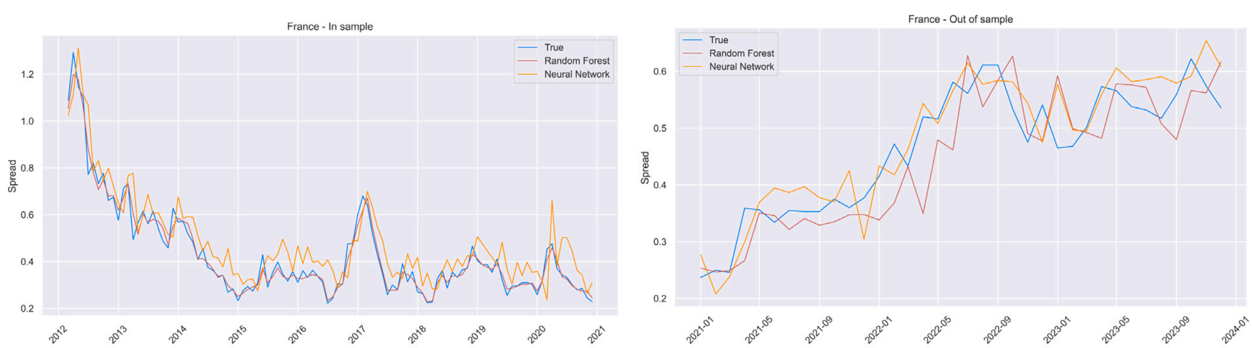

Fig. B.4. In-sample (left) and out-of-sample (right) time series for France.

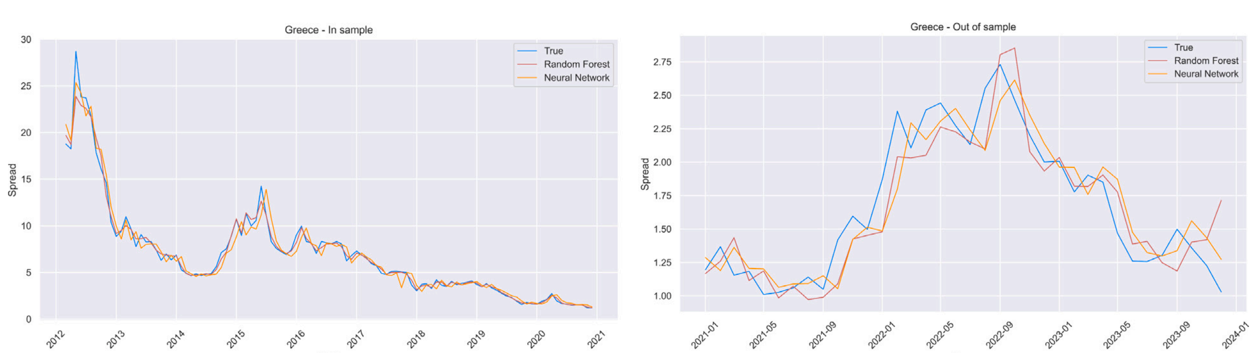

Fig. B.5. In-sample (left) and out-of-sample (right) time series for Greece.

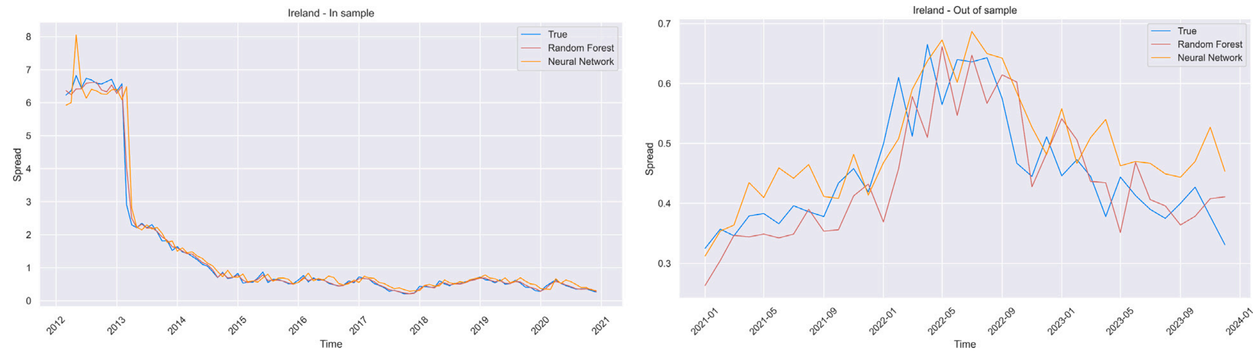

Fig. B.6. In-sample (left) and out-of-sample (right) time series for Ireland.

Fig. B.7. In-sample (left) and out-of-sample (right) time series for Italy.

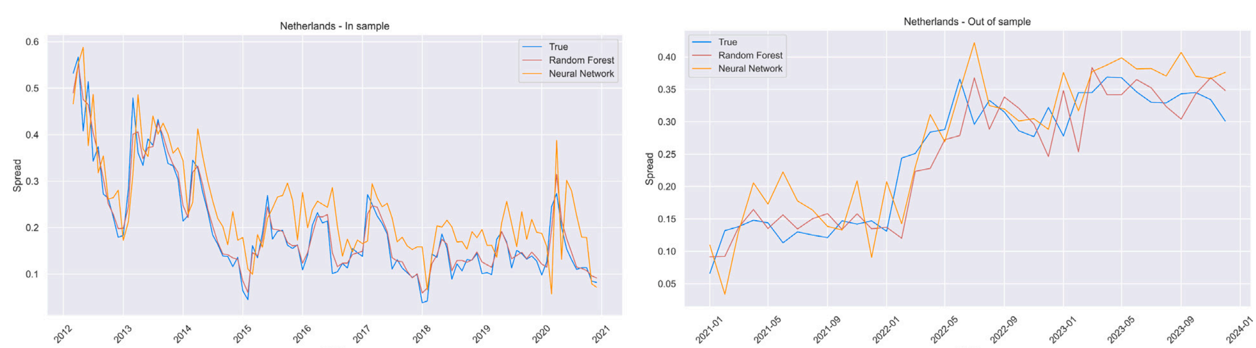

Fig. B.8. In-sample (left) and out-of-sample (right) time series for Netherlands.

Fig. B.9. In-sample (left) and out-of-sample (right) time series for Portugal.

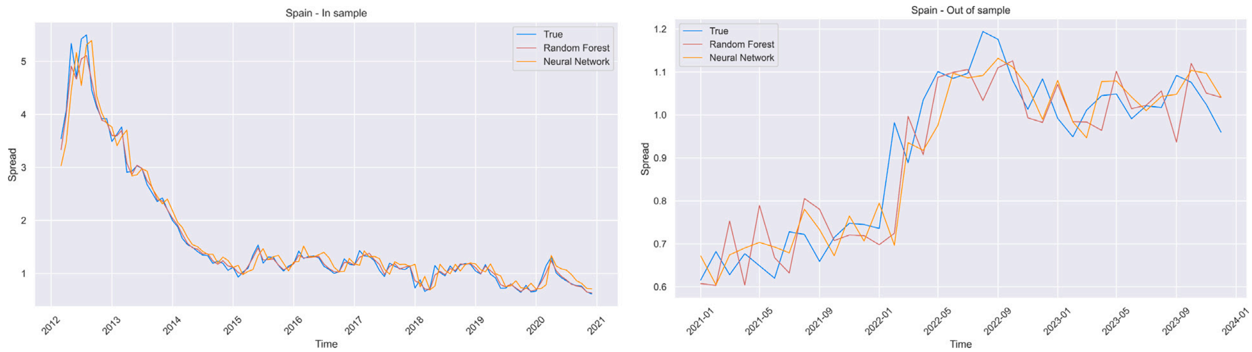

Fig. B.10. In-sample (left) and out-of-sample (right) time series for Spain.

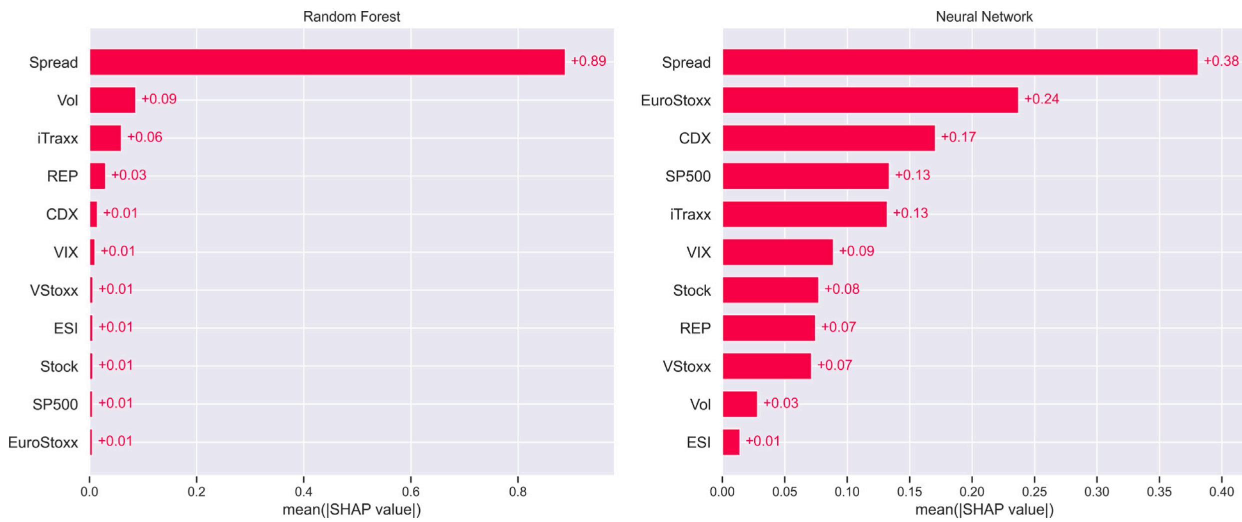

Fig. C.1. Mean SHAP values of the features in the Random Forest and Neural Network models, with REP measured as the ratio of renewable energy production to GDP.

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