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Climate risk and sovereign debt: country-level exposures and scarcity effects in green bonds

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Abstract

We investigate the role of climate risk in the Eurozone sovereign debt market, to evaluate the current pricing of different risk factors in the government spreads of each country. Particular attention is paid to differences between green and non-green bonds, in terms of reactions to climate risk. Weather variables are selected in line with the guidelines of Eurozone climate stress tests, and taken as proxies for acute and chronic physical risk, while EU carbon allowances are included to capture transition risk. Their significance is studied as potential drivers of mean spread variations and for their co-movement with spreads in the case of extreme events, to provide insights for climate risk management and financial policy, with the goal of enhancing the resilience and stability of the financial system. From both analyses, the same results emerge: climate risk is being priced by the market, but differently depending on the country, and green government bonds from different countries have a divergent reaction to climate risk factors. Dutch and French green spreads closely mirror their traditional counterparts, while German, Italian, and Spanish green bonds display lower reactivity. Various explanations are considered, including a "scarcity effect" linking the behavior of green bonds to their abundance relative to total outstanding government debt. Finally, the most relevant risk factors of each country are highlighted, comparing the results to known climate change challenges.

Keywords Financial stability · Climate risk · Green bonds · Sovereign debt · Government bonds · Physical risk · Transition risk

Jel Classification H63 · Q54 · E60 · C10 · G01

1 Introduction

Climate change has emerged as one of the greatest challenges of the current century for the global economy and for the stability of the financial sector. As reported in the 2024 Climate Risk Assessment by the European Environment Agency (EEA), Europe is the

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fastest warming continent in the world and climate risks not only threaten Europe's ecosystems and people's health, but also energy and food security, infrastructure, water resources, and financial stability. Additionally, extreme heat, drought, wildfires, and flooding are expected to worsen even under optimistic global warming scenarios, impacting the entire continent. European regulatory bodies have taken a leading role in introducing measures to assess the resilience of financial institutions and the broader economy to climate-related shocks, ranging from the 2020 Pilot Exercise on Climate Risk to the subsequent yearly Climate Stress Tests by the European Banking Authority (EBA).

The strong exposure of European market players to physical and transition risks, together with their awareness of climate change, make this market - and the Eurozone especially, due to its internal currency homogeneity - a promising case study for investigating market attitudes towards climate risk and green financial assets. Furthermore, due to the unchangeable nature of their geographic exposure, local government bonds are a particularly important asset class, as they can be expected to reflect climate risk more purely than corporate ones. In fact, while firms are able to relocate, countries do not have such a possibility.

In this work, we evaluate and compare the relationship of green and non-green bonds, issued by the same Eurozone governments, with climate risk. The goal of the analysis is two-fold. Firstly, it is to improve the understanding of current market attitudes to the climate change exposure of different countries, in order to contribute to a more accurate modeling and design of policy on climate risk, and to improve system-wide financial stability. Secondly, it is to investigate the potential contrasting treatment of green and traditional public debt on the part of the market with respect to climate risk. The methodology applied seeks to isolate and evaluate the climate risk embedded in the spreads of green and non-green government bonds, and to do so from multiple perspectives. First, its mean impact on the spread variations is studied, by including climate risk proxies as exogenous regressors of ARIMAX-GARCH models. Traditional, literature-based determinants of government bond risk are also included among the model exogenous regressors. The most relevant drivers for each country are then highlighted. Next, the joint tail behavior of green bonds and climate risk proxies is estimated through the use of non-parametric measures of tail dependence, in order to account for correlation patterns during extreme events. Both physical and transition risk are included, and proxies are selected on the basis of the prior literature, the EBA Climate Stress Tests and Exercises, the Climate Risk Landscape reports by the United Nations Environment Programme Finance Initiative, and the 2024 European Climate Risk Assessment. A differing market treatment between green and non-green bonds is uncovered, and potential explanations are put forth. Additionally, countries exposures are compared and contrasted, to evaluate the current pricing, on the part of the market, of climate risk in each country. The most relevant climate risk factors for each sovereign issuer are investigated and linked to known climate change challenges having already arisen on the corresponding territory.

The paper is organized as follows. Section 2 reviews the existing literature and identifies the contributions made by this work. Section 3 introduces the theoretical framework of the two-fold analysis, with subsection 3.1 describing the time series analysis of the spreads and subsection 3.2 focusing on the tail-dependence analysis.

Next, Section 5 presents the results of the analyses and Section 6 focuses on their implications for financial stability. Finally, Section 7 concludes.

2 Literature review

The financial literature includes a multitude of topics on climate risk, among which its impact on financial stability (as in Chabot and Bertrand (2023) and Karydas and Xepapadeas (2022)), the existence of a physical risk premium (evidenced in Allman (2021) and Bats et al. (2023)), the existence of a transition risk premium in corporate bonds (in Bats et al. (2023)) and equity markets (in Bolton and Kacperczyk (2021) and Po-Hsuan et al. (2023)), and the potential safe-haven properties of green assets (in Cepni et al. (2022)).

On the subject of financial stability, Chabot and Bertrand (2023), focus on financial institutions and propose a theoretical framework for the transmission of climate risks within the financial system. They find that transition risk, measured by Scope 3 greenhouse gas emissions, and physical risk negatively affect financial stability at the bank and system levels. Among the physical risk drivers, temperature anomalies, heat waves, wildfires and droughts are found to be of particular significance. We extend the analysis of climate risk to the treasury bond market, accounting for a different measure of transition risk - motivating our choice through econometric and financial arguments linked to the nature of our model - but ensuring that the most significant physical risk drivers identified in the study are included. Furthermore, we construct our methodology in order to disentangle two potential effects of climate risk: first, on the mean of treasury spread changes, our selected measure of credit risk, and second, on their extreme events. Finally, we include a focus on green assets, in order to uncover potential differences in their climate risk exposure.

As for Karydas and Xepapadeas (2022), they study the effect of climate change on asset prices and interest rates, in a model where tail events become more frequent and less predictable, raising the premium associated with climate risk. They find that this frequency change may not be fully reflected by the market risk premium. They also uncover that transition risk reduces the participation of brown assets in the market portfolio. We expand on their analyses of climate risk pricing by the market, but choose to study governments. We do this to focus on the inevitable component of physical risk, which cannot be avoided by governments - as, differently from firms, they are unable to relocate. Additionally, building on the result concerning the reduction in brown assets within the market portfolio, we seek to understand the market treatment of (and therefore appetite for) green and non-green bonds, ceteris paribus. We achieve this by comparing green and non-green bonds by the same entities.

The literature on physical risk premia includes Allman (2021), who identifies a premium in U.S. municipal bonds over corporate ones, tied to their inescapable exposure to sea level rise. We build on this and decide to focus on governments bonds, but instead aim to provide a comparison across countries and between assets of different greenness levels. Other work, including Bats et al. (2023) and Cepni et al. (2022), uses a textual analysis-based index of physical risk derived from news headlines. Our study includes a large number of physical risk proxies, which additionally are directly linked to weather variables. The goal is to increase alignment with the European regulatory environment and the 2024 European Climate Risk Assessment of the EEA, hopefully providing insights that can be interpreted directly.

As for transition risk, public institutions working for accelerating the transition towards a green economy use a system of rewards and penalties, for companies adopting green or non-green strategies. The optimal role and level of such policies is analyzed in Galeotti and Vannucci (2023). Different measures of it are considered, in the literature. Bolton and Kacperczyk (2021) and Po-Hsuan et al. (2023) find that transition risk is priced in the equity market, supporting the hypothesis that investor account for it and demand corresponding compensation. As risk proxies, they use carbon dioxide emissions and a broader measure of toxic emissions, respectively. Bats et al. (2023), instead, use a textual analysis-based indicator of transition risk and uncover that the corresponding premia in the corporate bond market exist, but are smaller than for physical risk and less significant. In order to build on these results, we incorporate a potential proxy for transition risk in our work and focus on the unexplored area of government bonds.

One final literature strand of relevance for our study is captured by Cepni et al. (2022), and concerns the role of green assets in climate risk mitigation. Importantly, using textual analysis-based measures of transition and physical risk, they find that green bonds stand out from other green assets in displaying reliable safe haven properties in the face of climate uncertainty, and do so more effectively than gold. This insight has particularly relevant implications for the attractiveness of green bonds, which, in Reboredo and Ugolini (2020) and Martiradonna et al. (2023), have also been found to provide diversification benefits with respect to a number of traditional investment sectors. Additionally, in Morelli and D'Ecclesia (2021), positive environmental performance is found to be a portfolio construction criterion that provides stabilization with regards to market risk, especially in periods of turmoil. For this reason, we include in our analysis a comparison of green and non-green bonds, and extend it to sovereign issuers. Additionally, we again consider different risk proxies from the study, in order to enable comparisons - across countries - of the weather variables having the greatest impact.

To our knowledge, this is the first analysis of both physical and transition risk carried out on government bonds, as well as the first to compare green and non-green treasuries in terms of their climate risk exposure.

3 Methodology

3.1 Time series analysis of bond spreads

The analysis begins with the yield-to-maturity (YTM) of the bonds. At time t, the YTM, $y_{b,t}$, of a bond b with maturity t_{N_b} is the discount rate that equates the present value of all future cash flows from the bond to its current price, denoted as $P_b(t, t_{N_b})$. The YTM contains the same information as the bond price but can be broken down into a risk-free yield, $y_{b,t}^{RF}$, and a spread, $s_{b,t}$

$$y_{b,t} = y_{b,t}^{RF} + s_{b,t}, \quad 0 \leq t \leq t_N.$$

Since the market risk-free yield is a macro-economic quantity, it is affected by changes in the expected inflation rate and in the expected real interest rate, while the spread depends on the credit risk of the issuer and on the liquidity of the bond. For this reason, the spreads are the focus of this analysis. They also have the advantage of representing issuer-specific risk without requiring the assumptions of credit risk models, thus reducing the model-dependence of the results. The $y_{b,t}^{RF}$ of bond b is the YTM of a bond having its same principal, coupon schedule, and maturity, but discounted on the risk-free curve. In this work, the risk-free rates are bootstrapped in Matlab from the EURIBOR Interest Rate Swap (IRS) curve and are taken as the same for all Eurozone governments in the sample, in order to enhance the comparability of the spreads across countries. By subtracting the $y_{b,t}^{RF}$ from the quoted end-of-day $y_{b,t}$, $0 \leq t \leq t_{N_b}$, the time series of spreads is obtained.

In order to recover the $y_{b,t}^{RF}$, we first construct synthetic risk-free bonds equivalent to each treasury bond in our sample, and price them every day of the original set of observations. Once the time series of the risk-free prices $P_b^{RF}(t, t_{N_b})$ of each bond is computed, the $y_{b,t}^{RF}$ are found for $0 \leq t \leq t_{N_b}$ as

$$\underset{y_{b,t}^{RF}}{\arg\min} \left(P_b^{RF}(t, N_b) - \sum_{j=1}^{N_b} \frac{c_b F_b}{(1 + y_{b,t}^{RF})^{t_j - t}} - \frac{F_b}{(1 + y_{b,t}^{RF})^{t_{N_b} - t}} \right)^2,$$

where c_b is the coupon rate of the treasury bond, and F_b is its face value.

When computing the prices $P_b^{RF}(t, t_{N_b})$, the risk-free discount rates with maturities corresponding to the cash flows of the bond, $r^{BMK}(t, t_j)$, $j = 1, ..., N_b$, are required. They are interpolated from the bootstrapped term structure of EURIBOR rates, which only includes a limited set of maturities (corresponding to the payment times of the quoted IRS contracts). This is done daily, for every t.

The selected scheme for the interpolation is the Nelson-Siegel-Svensson (NSS) model, from Dahlquist and Svensson (1996). It describes the term structure of spot continuously compounded rates, $r(\tau)$, by an expansion having four basis functions $F_j(\tau)$, $j = 0, ..., 3$, which represent the various components of a term structure. More precisely, we have that

$$r(\tau) = \beta_0 F_0(\tau) + \beta_1 F_1(\tau) + \beta_2 F_2(\tau) + \beta_3 F_3(\tau),$$

where $F_0(\tau)$ is the long-term level of the term structure, $F_1(\tau)$ its exponential decay, showing an upward or downward slope based on β_1's sign, $F_2(\tau)$ and $F_3(\tau)$ represent changes in its curvature, β_0, β_1, β_2, β_3 are the coefficients of expansion, and $\tau = t_j - t$ is the tenor of the rate. The NSS model parameters are fit via ordinary least squares on the continuously compounded rates equivalent to the $r^{BMK}(t, t_N)$ extracted from the swaps via bootstrapping.

3.1.1 The ARIMAX(p,d,q) model

Non-stationarity is detected in the time series of a majority of the spreads: they fail to reject the null hypothesis of the augmented Dickey–Fuller test (ADF) at the 10%, 5%, and 1% significance levels. Autocorrelation, non-normality and heteroskedasticity are also present in most spreads, through the Breusch-Godfrey, Jarque-Bera, and Breusch-Pagan Lagrange Multiplier tests, respectively. The ARIMAX model class is able to account for these conditions. Since the residuals are found to have excess kurtosis and to display heteroskedasticity, ARIMAX(p,d,q) models are fit to the time series of spreads of each bond b, $\{s_{b,t}\}_{t\in\mathbb{N}}$, with conditionally Student-t-distributed innovations. Heteroskedasticity and volatility clustering are incorporated through GARCH variances, for the time series that reject the null hypothesis of homoskedasticity of the Breusch-Pagan Lagrange Multiplier test. The potential drivers of the spread variations - including the climate risk factors - are included as exogenous regressors $X_{b,k}$, $k = 1, ..., n$. They are lagged of one period, in order to be known at time t. Their explanatory power is then evaluated by assessing the statistical significance of their coefficients. The resulting model is

$$\begin{aligned}
&\left(1-\sum_{i=1}^{p}\varphi_{b,i}L^i\right)(1-L)^d s_{b,t} = \theta_{b,0} + \left(1+\sum_{j=1}^{q}\theta_{b,j}L^j\right)\epsilon_{b,t} + \sum_{k=1}^{n}\alpha_{b,k}X_{b,k,t-1},\\
&\epsilon_{b,t}|\mathcal{F}_{t-1} \sim t_{\nu_b}(0,\sigma_{b,t}),\\
&\sigma_{b,t} = \sqrt{\frac{\nu_b-2}{\nu_b}h_{b,t}},\\
&h_{b,t} = \omega_b + \sum_{p=1}^{P_b}\psi_{b,p}\epsilon^2_{b,t-p} + \sum_{q=1}^{Q_b}\phi_{b,q}h_{b,t-q},
\end{aligned}$$

where L^i is the lag operator of order i, $\theta_{b,0}$ is a constant, $\epsilon_{b,t}$ is the model residual at time t of the b^{th} time series, $h_{b,t}$ is its conditional variance, $\sigma_{b,t}$ is the shape parameter of the corresponding Student t distribution, and ν_b are its degrees of freedom. The quantity $(1-L)^d s_{b,t}$ is the dependent variable of the model, and indicates the d-difference of the spreads. For $d = 0$, this is the spread level itself, namely $s_{b,t}$. For $d = 1$, this is the first difference, which in lag operator notation is $(1-L)s_{b,t} = s_{b,t} - s_{b,t-1}$. The value of d is the *order of integration* of the spreads. As for $\left(1-\sum_{i=1}^{p}\varphi_{b,i}L^i\right)$, it represents, in lag-operator notation, the auto-regressive component of the model. Each i^{th} element of the summation is a lag of order i of the dependent variable, having coefficient $\varphi_{b,i}$. The total number of auto-regressive lags is p and can change for each bond. If $p = 0$, there are no auto-regressive terms but only the dependent variable itself. The quantity $\left(1+\sum_{j=1}^{q}\theta_{b,j}L^j\right)\epsilon_{b,t}$ is instead the moving-average component of the model. Each j^{th} element of the summation is a lag of order j of the residual, having coefficient $\theta_{b,j}$. The total number of auto-regressive lags is q and can change for each bond. If $q = 0$, there are no moving-average terms but only the residual, as $(1+0)\,\epsilon_{b,t} = \epsilon_{b,t}$. The summation $\sum_{k=1}^{n}\alpha_{b,k}X_{b,k,t-1}$ holds the n total exogenous regressors of each bond b, observed at time $t-1$, namely one day before the independent variable of the model. Each $X_{b,k,t-1}$ is multiplied by a bond- and regressor-specific coefficient, $\alpha_{b,k}$.

Due to the presence of heteroskedasticity, the conditional variance $h_{b,t}$ follows a GARCH model, where the order (P_b,Q_b) can change for each bond b. The term ω_b is a constant, $\epsilon^2_{b,t-p}$ are the squared residuals, with lags from 1 to P_b and coefficient $\psi_{b,p}$. As for $h_{b,t-q}$, they are the conditional variances, with lags from 1 to Q_b and coefficient $\phi_{b,q}$.

The order of integration d is found, for every time series, by taking the first differences until the null hypothesis of the Augmented Dickey Fuller test is rejected at the 1% significance level. Afterwards, ARMAX(p,q) models are fit in Matlab on the stationary time series $(1-L)^d s_{b,t}$ via Maximum Likelihood. For every time series, the values of the lags p and q are found by fitting the models with all combinations of lag values, from 0 to a maximum of 8, and selecting the one with the lowest Bayes Information Criterion. The maximum number of lags is set to be the same as the one used in the Breusch-Godfrey test for autocorrelation.

The $X_{b,k}$, $k=1,...,n$ are also checked for stationarity and, if needed, their first differences are taken. Additionally, all time series are standardized, in order to avoid scale-related issues and enhance regressor comparability. Finally, potential multicollinearity issues are prevented by performing a test of variance inflation factors before fitting the models. This is done to ensure the reliability of the estimates.

In light of the presence of heteroskedasticity, one additional modeling alternative is considered: the ARIMAX-GARCHX class. GARCHX models expand the specification of the variance $h_{b,t}$ to also include lagged exogenous regressors, so that

$$h_{b,t} = \omega_b + \sum_{p=1}^{P_b} \psi_{b,p}\epsilon^2_{b,t-p} + \sum_{q=1}^{Q_b} \phi_{b,q} h_{b,t-q} + \sum_{k=1}^{n} \zeta_{b,k} X_{b,k,t-1}.$$

The regressors might play a role in impacting the variance of the spreads. The results are reported in Section 5.1.1.

3.2 Tail dependence analysis

The second part of the analysis focuses on the co-movement between extreme values of climate risk factors, and extreme values of treasury spreads. The starting point of the study are the standardized residuals of the bond spreads and of the climate-risk variables. The climate-risk variables and the reasons behind their selection are reported in detail in Section 4. The physical risk proxies are: drought and flood indicators, the non-seasonal component of average daily temperature, the non-seasonal components of average daily Eastward and Northward wind speed, and the Fire Weather Index (FWI), representative of wildfire risk. Transition risk is instead proxied by the log-returns of the carbon allowances of the EU Emissions Trading Scheme. Once recovered, the standardized residuals are used to compute non-parametric indicators of tail dependence.

3.2.1 The standardized residuals

The standardized residuals of the time series of bond spreads are obtained coherently with the modeling of Section 3.1. The estimated innovation terms are extracted from the ARIMAX models. They are then standardized by dividing them by the estimated conditional standard deviations.

The FWI and the de-seasonalized average daily Eastward and Northward wind speed are modeled as Ornstein-Uhlenbeck processes driven by pure jump Lévy processes, as in Benth et al. (2018) and Benth et al. (2021).

On the other hand, the flood and drought indices are modeled as Cox-Ingersoll-Ross (C.I.R.) processes. This selection is based on the non-normal nature of the associated time series. In contrast, pure jump Lévy processes are employed for the fire and wind indices. This choice is motivated by the necessity to accommodate a non-zero probability of the event occurring when these indices exhibit an increment of zero.

Therefore, given a probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$, with $\mathbb{P}$ the physical risk measure, the dynamics of the FWI and the de-seasonalized average daily Eastward and Northward wind speed are

$$\begin{aligned} d\gamma_{i,t} &= -k_i\gamma_{i,t}dt + dL_{i,t}, \\ \gamma_{i,t} &= \gamma_{i,t_0}e^{-k_i(t-t_0)} + \int_{t_0}^{t} e^{-k_i(t-u)}dL_{i,u}, \end{aligned} \tag{1}$$

where $L_{i,t}$, with $i = 1, 2, 3$, are independent compound Poisson processes with intensity λ_i and exponential jump size of expected value η_i, and k_i is the speed of mean reversion. Finally, γ_{i,t_0} is the known exit point of the process. The dynamics of the flood and drought indices are represented by

$$d\gamma_{i,t} = k_i(\theta_i - \gamma_{i,t})dt + \sigma_i\sqrt{\gamma_{i,t}}dW_{i,t}, \tag{2}$$

where k_i is the speed of mean reversion, θ_i is the long-term level of the process, σ_i is the volatility, $\sigma_i\sqrt{\gamma_{i,t}}$ is the standard deviation, and $W_{i,t}$, with $i = 0, 4, 5$, are independent standard Wiener processes.

The standardized residuals of the FWI and the non-seasonal component of average daily eastward and northward wind speed are recovered by fitting the pure-jump-Lévy-driven Ornstein-Uhlenbeck processes. The SDE in Eq. (1) is discretized as follows

$$\begin{aligned} \gamma_{i,t+\Delta t} - \gamma_{i,t} &= -k_i\gamma_{i,t}\Delta t + L_{i,t+\Delta t} - L_{i,t} \\ \gamma_{i,t+\Delta t} &= (1 - k_i\Delta t)\gamma_{i,t} + \Delta L_{i,t} \\ \gamma_{i,t+\Delta t} &= (1 - k_i\Delta t)\gamma_{i,t} + \Delta L_{i,t} \pm \mathbb{E}[\Delta L_{i,t}] \\ \gamma_{i,t+\Delta t} &= \mathbb{E}[\Delta L_{i,t}] + (1 - k_i\Delta t)\gamma_{i,t} + \Delta L_{i,t} - \mathbb{E}[\Delta L_{i,t}] \\ \gamma_{i,t+\Delta t} &= \mathbb{E}[\Delta L_{i,t}] + (1 - k_i\Delta t)\gamma_{i,t} + \xi_{i,t}, \end{aligned}$$

where $\Delta L_{i,t} = L_{i,t+\Delta t} - L_{i,t}$ and $\xi_{i,t} = \Delta L_{i,t} - \mathbb{E}[\Delta L_{i,t}]$, meaning that $\mathbb{E}[\xi_{i,t}] = 0$, for $i = 1, 2, 3$. Since $L_{i,t}$ are independent compound Poisson processes with intensity

λ_i and exponential jump size of expected value η_i, we have that $\mathbb{E}[\Delta L_{i,t}] = \lambda_i \eta_i \Delta t$ and $Var(\xi_{i,t}) = Var(\Delta L_{i,t}) = 2\lambda_i \Delta t \eta_i^2$. The standardized residuals $\{\hat{\epsilon}_{i,t}\}_{t\in\mathbb{N}_0}$ are then recovered by running an AR(1) regression on the $\{\gamma_{i,t}\}_{t\in\mathbb{N}_0}$, and by dividing the resulting $\{\hat{\hat{\xi}}_{i,t}\}_{t\in\mathbb{N}_0}$ by the residual standard deviation.

The residuals of the flood and drought indices are found after fitting C.I.R. processes to the data. More precisely, Eq. (2) is discretized as follows

$$\begin{aligned}
\gamma_{i,t+\Delta t} - \gamma_{i,t} &= k_i(\theta_i - \gamma_{i,t})\Delta t + \sigma_i \sqrt{\gamma_{i,t}\Delta t}\epsilon_{i,t} \\
\frac{\gamma_{i,t+\Delta t} - \gamma_{i,t}}{\sqrt{\gamma_{i,t}}} &= \frac{k_i\theta_i\Delta t}{\sqrt{\gamma_{i,t}}} - k_i\sqrt{\gamma_{i,t}}\Delta t + \sigma_i\sqrt{\Delta t}\epsilon_{i,t},
\end{aligned}$$

where $i = 4, 5$ and the innovations are $\epsilon_{i,t} \sim N(0, 1)$, i.i.d., with $t \in \mathbb{N}_0$. The parameters k_i and θ_i are estimated by minimizing

$$\arg\min_{k_i,\theta_i} \sum_{t=0}^{T} \left(\frac{\gamma_{i,t+\Delta t} - \gamma_{i,t}}{\sqrt{\gamma_{i,t}}} - \frac{k_i\theta_i\Delta t}{\sqrt{\gamma_{i,t}}} + k_i\sqrt{\gamma_{i,t}}\Delta t \right)^2.$$

The standardized residuals $\{\hat{\epsilon}_{i,t}\}_{t\in\mathbb{N}_0}$ are then recovered from the model residuals.

In order to model the non-seasonal component of daily mean temperature we rely on the approach by Benth and Saltyte-Benth (2012) which is introduced for the pricing of weather derivatives written on temperature indices. The temperature process, T_t, $t \in \mathbb{R}^+$, is assumed to be of the form

$$T_t = \Lambda_t + \gamma_t,$$

where Λ_t is a continuous bounded function representing seasonality and γ_t is the non-seasonal component of daily mean temperature. It is a Continuous-time Auto-Regressive Moving Average (CARMA) process, of lag orders $p, q \in \mathbb{N}_0$ with $q < p$. Under $\mathbb{P}$, γ_t has the following state-space representation:

$$\gamma_t = \mathbf{b}^\top \mathbf{X}_t, \tag{3}$$

$$d\mathbf{X}_t = \mathbf{A}\mathbf{X}_t dt + \mathbf{e}_p dL_t, \tag{4}$$

where L_t is a Lévy process, $\mathbf{X}_t$ is an $\mathbb{R}^p$-valued stochastic process, $\mathbf{A} \in \mathbb{R}^{p\times p}$ is a matrix of coefficients, and $\mathbf{b}, \mathbf{e}_p \in \mathbb{R}^p$, such that:

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ -a_p & -a_{p-1} & -a_{p-2} & \cdots & -a_1 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_{p-2} \\ b_{p-1} \end{bmatrix}, \quad \mathbf{e}_p = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

and $\mathbf{A} = -a_1$ for $p = 1$. The solution of the stochastic differential equation starting at time $t_0 \geq 0$ is given by

$$\mathbf{X}_t = e^{\mathbf{A}(t-s)}\mathbf{X}_{t_0} + \int_{t_0}^{t} e^{\mathbf{A}(t-u)}\mathbf{e}_p \, dL_u, \quad t_0 < t.$$

The increments of the Lévy process follow a Normal Inverse Gaussian (NIG) distribution, which is chosen to accommodate the leptokurtic and skewed nature of the underlying data. The CARMA(p,q) processes are fit, with lag orders selected based on the observation of the partial autocorrelation functions. The SDE in Eq. (3) is discretized following Lavagnini (2020). For $p = 2$ and $q = 0$, we have

$$\begin{aligned}
\gamma_{i,t+2\Delta t} &= (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} + \Delta t(L_{i,t+2\Delta t} \\
&\quad - L_{i,t+\Delta t}) \\
&= (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} + \Delta t(\Delta L_{i,t+\Delta t} \\
&\quad \pm \mathbb{E}[\Delta L_{i,t+\Delta t}]) \\
&= \Delta t\mathbb{E}[\Delta L_{i,t+\Delta t}] + (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} \\
&\quad + \Delta t\xi_{i,t+\Delta t},
\end{aligned} \tag{5}$$

where $i = 6$, $\Delta L_{i,t+\Delta t} = L_{i,t+2\Delta t} - L_{i,t+\Delta t}$ and $\Delta L_{i,t+\Delta t} \sim NIG(\alpha, \beta, \delta, \mu)$, with $t \in \mathbb{N}_0$, where μ is the location parameter, α the tail dependence, β the asymmetry, and δ the scale of the distribution. Furthermore, $\xi_{i,t+\Delta t} = \Delta L_{i,t+\Delta t} - \mathbb{E}[\Delta L_{i,t+\Delta t}]$, meaning that $\xi_{i,t+\Delta t} \sim NIG(\alpha, \beta, \delta, \frac{-\delta\beta}{\sqrt{\alpha^2-\beta^2}})$ and $\mathbb{E}[\xi_{i,t+\Delta t}] = 0$. The standardized residuals $\{\hat{\epsilon}_{i,t}\}_{t\in\mathbb{N}_0}$ are recovered via maximum-likelihood estimation of Eq. (5) and by dividing the resulting $\{\hat{\xi}_{i,t}\}_{t\in\mathbb{N}_0}$ by the residual standard deviation. More details are reported in Appendix B.

As for the spot EU carbon allowance prices, the study by Daskalakis et al. (2009) compared multiple continuous-time models for their price dynamics, found the Merton (1976) jump-diffusion model to provide the most accurate fit. Therefore, the carbon allowance price follows

$$\frac{dS_{i,t}}{S_{i,t}} = (\mu_i - \lambda_i k_i)dt + \sigma_i dW_{i,t} + dL_t, \tag{6}$$

$$\begin{aligned}
S_{i,t} &= S_{i,t_0} \exp\left\{\left(\mu_i - \lambda_i k_i - \frac{\sigma_i^2}{2}\right)(t - t_0) + \sigma_i(W_{i,t} - W_{i,t_0})\right\} \prod_{j=N_{t_0}}^{N_t} Y_j \\
&= S_{i,t_0} \exp\left\{\left(\mu_i - \lambda_i k_i - \frac{\sigma_i^2}{2}\right)(t - t_0) + \sigma_i(W_{i,t} - W_{i,t_0}) + \sum_{j=N_{t_0}}^{N_t} y_j\right\}
\end{aligned} \tag{7}$$

where $i = 7$, μ_i is the expected return of the asset per unit of time, σ_i is the volatility, and $W_{i,t}$ is a standard Wiener process. $L_t = \sum_{j=1}^{N_t}(Y_j - 1)$ is a compound Poisson process with Poisson process N_t having rate λ, which represents the average number of jumps per year, and i.i.d. jumps Y_j following a lognormal distribution. Additionally, $k = \mathbb{E}[Y_j - 1]$, and $y_j = \ln(Y_j)$ is normally distributed. $W_{i,t}$, N_t, and Y are assumed to be mutually independent. The discretized log-returns $\gamma_{i,t}$ of carbon allowance prices are then

$$\gamma_{i,t+\Delta t} = \log\left(\frac{S_{i,t+\Delta t}}{S_{i,t}}\right) = \left(\mu_i - \lambda_i k_i - \frac{\sigma_i^2}{2}\right)\Delta t + \sigma_i\sqrt{\Delta t}\cdot Z + \sum_{j=N_t}^{N_{t+\Delta t}} y_j, \quad (8)$$

where $Z \sim N(0, 1)$. The returns are conditionally normally distributed, given the knowledge of $N_{t+\Delta t} - N_t$. Unconditionally, they follow a Poisson mixture of normal distributions. More details, including the unconditional probability density function, are reported in Appendix B. The standardized residuals $\{\hat{\epsilon}_{i,t}\}_{t\in\mathbb{N}_0}$ are finally recovered via maximum-likelihood estimation of Eq. (8), by removing the mean and dividing the resulting residuals by their standard deviation.

3.2.2 Non-parametric tail dependence analysis

We compute the non-parametric tail dependence between the extreme values of the bond spreads and each climate-risk proxy, individually, in order to examine their likelihood of simultaneously experiencing extreme events. We utilize a non-parametric estimation, directly examining the empirical distribution of data points, in order to avoid assumptions on the underlying joint distribution of the variables. Those assumptions, in the form of the choice of a copula function, would influence the output of a parametric index of tail dependence.

As defined in Schmidt and Stadtmüller (2006), the non-parametric q-quantile (tail) dependence of n random variables, X_1, X_2, ..., X_n, is:

$$\lambda_q = \begin{cases} \frac{1}{qT}\sum_{t=1}^{T} 1\left\{u_{X_1,t} \le q, u_{X_2,t} \le q, ..., u_{X_n,t} \le q\right\}, & 0 < q \le 0.5 \\ \frac{1}{(1-q)T}\sum_{t=1}^{T} 1\left\{u_{X_1,t} > q, u_{X_2,t} > q, ..., u_{X_n,t} > q\right\} & 0.5 < q \le 1, \end{cases}$$

where $u_{X_j,t} = \hat{\mathrm{F}}_{X_j}\left(\hat{\epsilon}_{X_j,t}\right)$, with $\hat{\mathrm{F}}_{X_j}$ being the empirical cumulative distribution function of X_j, $j = 1, 2, ..., n$, evaluated in its observed value at time t, $\hat{\epsilon}_{X_j,t}$. This indicator measures the proportion of occurrences, in the sample period, in which extreme realizations of the n random variables happen simultaneously. The realizations are deemed to be *extreme* whenever falling in the q-quantile (tails) of the empirical cumulative distribution functions of the corresponding random variables. The value of the index ranges from zero to one: zero indicates that tail events never occurred simultaneously for all random variables involved, while a value of one indicates that the extreme events of all random variables always occurred simultaneously.

We are interested in observing the results grouped by issuer, and in dividing them between green and non-green bonds.

An initial attempt is made, in which the non-parametric tail dependence is computed simultaneously for all bond spreads of one type (green or non-green), and each climate variable. If the number of green bonds by an issuer is n, and the number of non-green bonds is m, then, for every climate risk proxy and for each issuer, the index of tail dependence is computed twice. First, it is computed between $n+1$ random variables: the n green bond spreads and the one climate risk proxy. Next, it is computed between $m+1$ random variables: the m non-green bond spreads and the one climate risk proxy. The tail dependence is computed on the longest window of time during which all bonds are observable. Finally, for every index, confidence intervals at a 95% significance level are obtained via bootstrapping. The results, however, are strongly affected by the size of n and m. As the number of bond spreads by the same issuer increases, a low level of connection of any one of them - due to differences in the liquidity, responsiveness or demand of the underlying bond - forces the index to drop to zero. This can hide the real level of tail dependence between all other bond spreads and the climate variable at hand.

For this reason, we instead choose to compute two-dimensional non-parametric indices of tail dependence, having one climate variable, on one side, and each individual bond spread, on the other. Again, confidence intervals at a 95% significance level are obtained via bootstrapping for every index. We then group them by issuer and divide them according to the greenness of the bonds underlying the spreads.

4 Selection of the exogenous explanatory variables

The exogenous explanatory variables include proxies for climate risk, as well as traditional determinants of government credit risk. The latter are selected on the basis of the past literature and included in order to account for all known drivers of treasury-spread variations. A summary of the final choice of exogenous regressors and of the corresponding data sources is reported in Table 4. Section 4.1 describes in detail the data sources used in the present work.

The potential proxies for climate risk are drawn from the existing literature, EBA Climate Stress Tests and Exercises, Climate Risk Landscape reports by the United Nations Environment Programme Finance Initiative, and the 2024 European Climate Risk Assessment. The selection of the data representing each variable strongly considers its granularity, given the greater explanatory power of higher-frequency data in an analysis of this type.

The importance of drought and flood risks is highlighted in Chabot and Bertrand (2023) and in the Climate Stress Test conducted by European Central Bank (2022). Among the available climate variables that are connected to them, two potential proxies are found: the Combined Drought Indicator and the Soil Moisture Index Anomaly (SMA), both sourced from the Copernicus European Drought Observatory. The SMA denotes the deviation from typical water availability during the same period of the year. It is derived from the daily soil water content, which is used to calculate the Soil Moisture Index (SMI). The SMI averages the daily soil moisture across four earth surface layers from wilting point (SMI value of 0, indicating severe dryness) to field capacity (SMI value of 1, denoting the soil's inability to absorb more water). The daily SMA is then determined by standardizing the daily SMI using its long-term mean and standard deviation over the corresponding period. It is expressed in standard deviation units and values below -1 serve as proxies for drought anomalies, while those above 1 indicate flood risk proxies.

We also include the non-seasonal component of the average daily wind speed, focusing on both the Zonal (eastward) and Meridional (northward) wind components at a vertical height of 10m. This aspect plays a crucial role in renewable energy production and can represent the impact of storms, hurricanes and typhoons - which are risk factors highlighted in the Climate Risk Landscape report from the United Nations Environment Programme Finance Initiative (Carlin et al. 2023).

Following again the risk drivers outlined in Carlin et al. (2023), and also in line with the results in Chabot and Bertrand (2023), we acknowledge the need to account for wildfire risk. As a proxy, we use the Copernicus Fire Weather Index (FWI). This index, available on a daily basis, considers the impact of fuel moisture (linked to humidity and 24-hour accumulated precipitation) and wind. A higher FWI value indicates more favorable meteorological conditions for triggering a wildfire.

Finally, as an indicator of chronic physical risk, we propose the non-seasonal component of average daily temperature. It is tied to the dynamics of the demand for energy and affects worker productivity.

As for transition risk, the EU-wide pilot exercise on climate risk European Banking Authority (2021) and the Climate Stress Test by the European Central Bank (2023) focuses on greenhouse gas emissions intensity, to evaluate an issuer's exposure. These quantities make reference to Scope 1, Scope 2, and Scope 3 emissions, which are given formal definitions in points (1)(e)(i) to (iii) of Annex III to Regulation (EU) 2016/1011 of the European Parliament and Council (2016):

1. Scope 1 carbon emissions are "*generated from sources that are controlled by the company that issues the underlying assets*";
2. Scope 2 carbon emissions derive from the "*consumption of purchased electricity, steam, or other sources of energy generated upstream from the company that issues the underlying assets*";
3. Scope 3 carbon emissions include "*all indirect emissions that are not covered by points (i) and (ii) that occur in the value chain of the reporting company, including both upstream and downstream emissions, in particular for sectors with a high impact on climate change and its mitigation*";

The rationale behind using emissions as a proxy for transition risk is that highly polluting firms, or firms depending on emission-heavy production inputs or energy sources, are more affected by changes in the components of transition risk: regulatory environment, technological advances, and consumer preferences. However, there are two drawbacks to using this type of variable. The first is due to the nature of the data: estimates, even when provided by specialized entities such as MSCI, Refinitiv EIKON and Urgentem, rely on self-disclosures on the part of the firm: annual corporate, sustainability or social responsibility reports and information on company websites. However, problems related to low data availability and "extreme discrepancies" in the estimates given by different providers have been highlighted by the Joint Research Centre (JRC), the European Commission's science and knowledge service, in Papadopoulos (2022). Previous findings included Klaaßen and Stoll (2021), who uncovered that companies reported different Scope 3 emission figures across different channels, incompletely applied some criteria for emitting activities, or even omitted relevant Scope 3 categories.

The second limitation is that emissions data is available with a yearly periodicity, which is insufficient for the purposes of our study,

For this reason, instead of aggregating values of firm emissions by country, in order to obtain a local estimate for each government, we consider alternative proxies for transition risk, and select exclusively the one with the greater explanatory power. The first, as in Livieri et al. (2023), are the log-returns of EU carbon allowances, the permits that allow companies part of the EU Emissions Trading Scheme to emit a fixed amount of CO2 in the atmosphere. They are quoted contracts whose variable market price reflects the cost of reducing emissions and should increase when stricter policies are enacted, negatively impacting high-pollutant companies. The second potential proxy is the integrated volatility of futures contracts on carbon allowances, with a one-year maturity.

Concerning the traditional determinants of government bond spreads, they all relate to the country's overall health and solvency. In particular, the main elements of interest are the fiscal position of the country, broader macroeconomic factors, such as international competitiveness and performance of the economy, and global risk aversion indicators. The body of literature on this subject is quite extensive, and the variables that have been considered throughout the years are many. The selection for the purpose of this paper is primarily based on seminal studies, and on research and reports published by working groups internal to regulatory bodies: Afonso et al. (2015), Arghyrou and Kontonikas (2012), Beber et al. (2009), Bernoth et al. (2012), Collin-Dufresne et al. (2001), and Giordano et al. (2012). This is done in order to maintain the overall alignment of this study with the stated interests and goals of regulatory authorities.

The fiscal position of the country, similarly to the leverage ratio of a firm, is proxied by *government consolidated gross debt as a percentage of GDP* and by the *financial net worth* (FNW), which is the difference between the financial assets and the liabilities of a government. Additionally, following Giordano et al. (2012), *inflation* is included for its effect on debt servicing costs. The inflation index based on the all-item Harmonized Index of Consumer Price (HIPC) is considered.

The health of the country's economy, as in Afonso et al. (2015), is represented by the *industrial production index*, which measures changes in the price-adjusted output of industry. This is done in line with the evidence in the literature of government debt becoming riskier in times of economic slowdown (as in Bernoth et al. (2012)). A further variable traditionally representative of economic performance is *GDP growth rate*; it is therefore also included. The log-returns of each country's main *stock market index* are taken as a final proxy for the prevailing business climate. The indices are the CAC 40 for France, the DAX 30 for Germany, the FTSE MIB for Italy, the AEX for the Netherlands, and the IBEX-35 for Spain.

The international competitiveness of the economy is captured by *real effective exchange rate* (REER), which measures the evolution of the real value of a country's currency against that of its trading partners. The empirical significance of real exchange rates in explaining spreads in the EMU area has been confirmed in Arghyrou and Kontonikas (2012). An additional variable of interest is the *current account balance*, representative of the difference between the exports and imports of goods, services, and international transfers of capital.

The *implied stock market volatility index (VIX)* is also included, as a gauge of global risk appetite. It is frequently used in studies of Euro area government bond spreads, as for example Beber et al. (2009) and Afonso et al. (2015).

Furthermore, the liquidity of the government debt is approached from two different perspectives: the first relates to each individual bond. For this purpose, we use *closing percent quoted bid-ask spread* as a proxy. The second, on the other hand, relates to overall market size and is the *proportion of the debt of all Eurozone countries represented by each country's public debt*.

Finally, for their impact on debt servicing costs, prevailing interest rates are also included. In particular, this is done by taking as regressors the changes in *EURIBOR rates*, and in the *convexity* and *slope* of their term structures. It is necessary to select the tenor of the EURIBOR RATES, so multiple alternatives are considered: a fixed one for all bonds, or a different one for each individual bond, matched either to its maturity or to its duration.

As for the slope of the yield curve, the usual choice of proxy found in the literature, as in Collin-Dufresne et al. (2001), is the difference between the benchmark yield of a long maturity (often 10 years) and one with a shorter one. The convexity, instead, is often proxied by the square of the benchmark yield with a predetermined tenor. Again, the tenor can either be fixed, or matched to the maturity or to the duration of each bond. However, given that the NSS interpolation scheme has coefficients β_1 and β_2, which affect the slope and the curvature basis functions respectively, we also consider them as potential proxies. All alternatives are used individually as regressors, ceteris paribus.

4.1 Data

The sample in this study is comprised of sovereign bonds from Eurozone countries, within the time frame going from 01/01/2014 to 27/03/2023, and which are all active as of the last day of the sample period. In order to remove the impact of exchange rate risk, which is not of interest for the present work, we only consider Euro-denominated bonds. Furthermore, the selection of countries is restricted to those having issued at least one sovereign green bond at the time of the analysis and, for improved estimator convergence, only choose bonds for which a minimum of 100 observations is present. For this reason, while the number of issues of green bonds is substantially lower than that of traditional bonds, for all countries, the length of the time series of each green bond ensures that statistical inference performed on it is reliable. Therefore, when looking at aggregate results, the lower number of green bonds in the sample should not be interpreted as a limitation on the accuracy of the results. It is however a limit on the comparability of average measures across green and non-green bonds of the same issuer, as proportions take on extreme and less nuanced values when the numerator is very small. The final sample is described in Table 1. More details about the bonds, such as type, average coupon rate, average redemption value and average redemption date, are available in Tables 2 and 3, for green and non-green bonds, respectively. The

Table 1 Number of government bonds in the sample

Country	Green	Non-green
France	2	48
Germany	5	77
Italy	2	333
Netherlands	1	24
Spain	1	147

exogenous regressors under study and the corresponding data sources are summarized in Table 4.

4.1.1 Financial and macroeconomic data

Data on bond bid, ask, and mid prices, bond YTMs, IRS rates (IBA EUR IRS ISDAFIX DELAYED - MIDDLE RATE), the VIX index, national stock market indices, and EU carbon allowance prices is taken from Refinitiv Datastream. The Industrial Production Index is the seasonally and calendar-day adjusted NACE r2 B-D rate of change from the *sts_esms* dataset provided by Eurostat. The seasonally and calendar-day adjusted rate of growth of the Gross Domestic Product at market prices (B1GQ) is taken from the *namq_10_gdp* dataset, also provided by Eurostat. The Financial Net Worth (BF90) is taken from the Eurostat dataset *gov_10q_ggfa*, with reference to the S.13 sector, defined in the European system of accounts (ESA2010), paragraph 2.111 as the general government sector as consisting *"of institutional units which are non-market producers whose output is intended for individual and collective consumption, and are financed by compulsory payments made by units belonging to other sectors, and institutional units principally engaged in the redistribution of national income and wealth"*. Government consolidated gross debt (GD) as a percentage of GDP (PC_GDP), again of sector S.13, is taken from the *gov_10q_ggdebt* Eurostat dataset. The share of each country's public debt (GD) over the total debt outstanding in the euro area (EA19) is also taken for sector S.13, from the *gov_10q_ggdebt* Eurostat dataset. The monthly Current account balance is taken by considering as commercial partner the rest of the world (WRL_REST). It corresponds to variables bop_item: CA with stk_flow: BAL of the Eurostat dataset *bop_c6_m*. The monthly Real Effective Exchange Rate, which measures the evolution of the real value of the Euro against the basket of the trading partners of each country is provided by Bruegel. The rate of change in the inflation rate, corresponding to the all-items HICP, (cp00), is taken from the *PRC_HICP_MMOR* Eurostat dataset.

4.1.2 Climate data

The Copernicus European Drought Observatory provides the time series of the daily SMA, while the daily FWI is made available in the Copernicus *Fire danger indicators for Europe from 1970 to 2098 derived from climate projections* dataset. The hourly eastward and northward wind speed, expressed in metres per second and taken at a

Table 2 Features of green bonds in the sample, by country

	France	Germany	Italy	Netherlands	Spain
Bond type	Fixed-coupon: 2	Fixed-coupon: 5	Fixed-coupon: 2	Fixed-coupon: 1	Fixed-coupon: 1
Avg. coup. rate	1.125%	0.26%	2.75%	0.5%	1.0%
Avg. red. value	100.0	100.0	100.0	100.0	100.0
Avg. red. date	24/12/2041	14/04/2033	29/04/2040	15/01/2040	30/07/2042

Table 3 Features of non-green bonds in the sample, by country

	France	Germany	Italy	Netherlands	Spain
Bond type	Zero-coupon: 48	Zero-coupon: 68, Fixed-coupon: 9	Zero-coupon: 210, Fixed-coupon: 106, Floating: 17	Zero-coupon: 22, Fixed-coupon: 2	Zero-coupon: 132, Fixed-coupon: 15
Avg. coup. rate	0%	0.144%	2.641%	2.75%	0.89%
Avg. red. value	100.0	100.0	100.0	100.0	100.0
Avg. red. date	24/12/2036	26/06/2032	18/01/2034	21/09/2037	24/07/2038

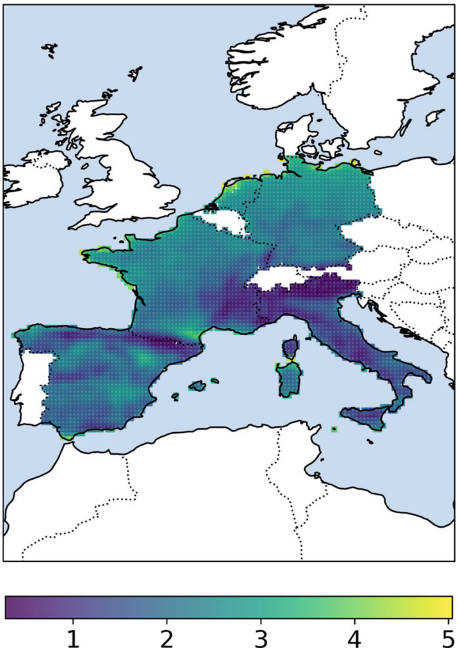


Fig. 1 Eastw. wind speed (m/s). Average daily values of climate variables by country, over the sample period

height of 10 metres, as well as the hourly temperature, expressed in Kelvin degrees and converted to Celsius, taken at a height of 2 metres, are available in the Copernicus *ERA5 hourly data on single levels from 1940 to present* database. They hourly values are averaged daily and on the latitude and longitude coordinates, converted to the EPSG:4326 Geodetic coordinate system, which are within the boundaries of each country.

Figures 1-6 show the maps of the sample-period average of each weather variable. Only countries that are included in the present study are shown. Average daily eastward and northward wind speed are plotted in Figures 1 and 2, respectively. The averages are taken on the absolute values (since the sign conveys information about wind direction, which is superfluous for our study). At a first glance, Italy appears to be the country with the lowest average values, while France, Germany, and the Netherlands have the highest. Figure 3 shows the FWI index. The countries with the highest average wildfire risk are Italy and Spain, with southern areas being the most exposed.

Figures 4 and 5 display the average drought and flood indices, respectively. Similarly to what is done in Section 3.1, the values of the drought index are taken as the absolute value of the observations below the wilting point in the SMA index, for ease of interpretation. Due to this, greater index values indicate greater levels of risk. In the maps, the extreme observations have been capped at 1, so that the variability at the lower end of the spectrum is not erased. All countries show concentrations of high values in a number of smaller areas, for both drought and flood risk. However, concerning drought risk, Italy strikes as the most affected country. Finally, Figure 6 shows average the daily temperature. Unsurprisingly, higher values are observed at lower latitudes.

Fig. 2 Northw. wind speed (m/s)

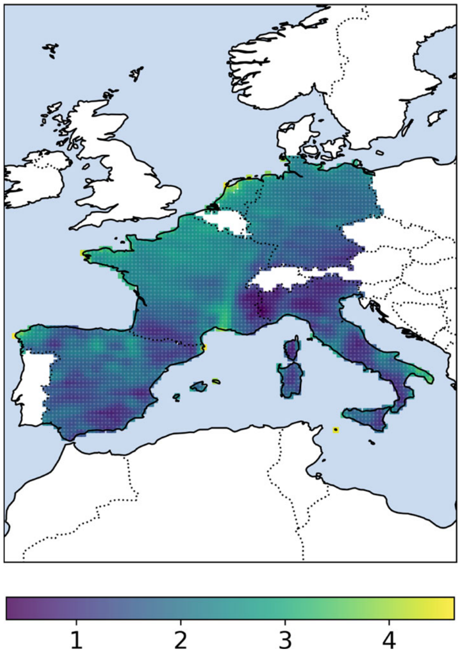


Fig. 3 Fire Weather Index

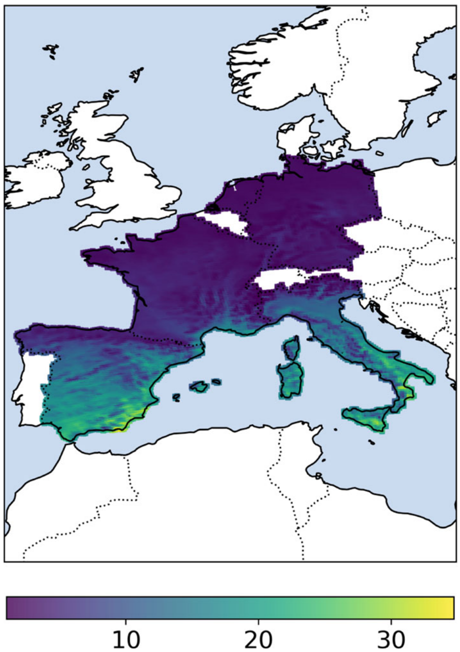


Fig. 4 Drought index

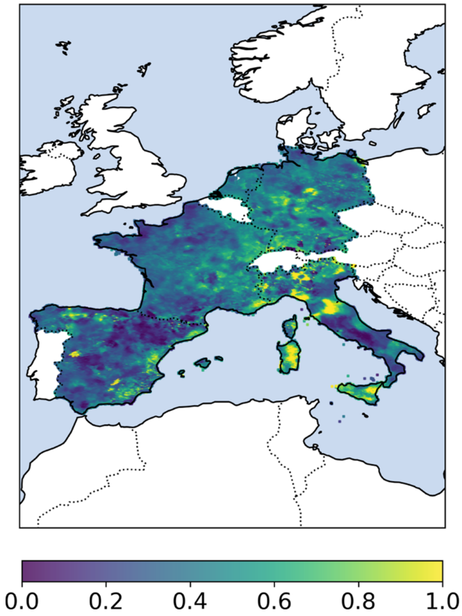


Fig. 5 Flood index

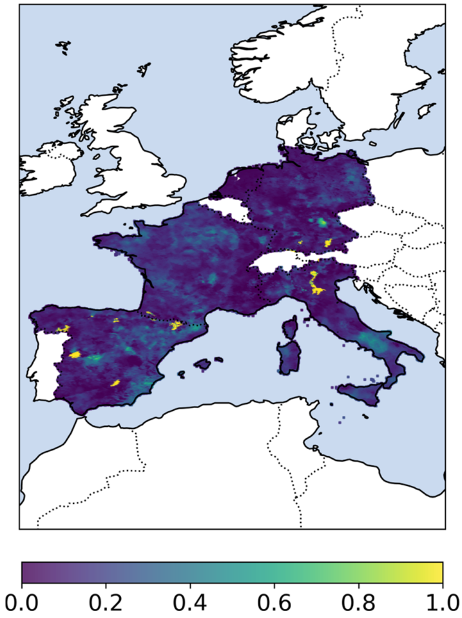
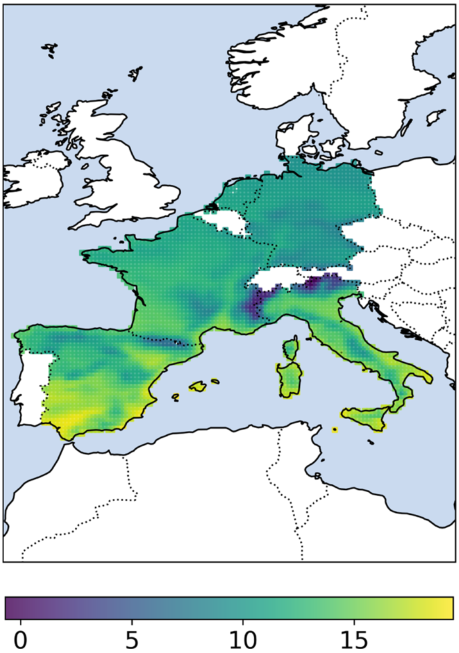


Table 4 Summary of exogenous regressors and of corresponding data sources

Variable	Reason for inclusion	Data source
Nonseasonal component of average daily eastward wind	Physical climate risk	Copernicus Datastore (Dataset: ERA5 hourly data on single levels from 1940 to present)
Nonseasonal component of average daily northward wind	Physical climate risk	Copernicus Datastore (Dataset: ERA5 hourly data on single levels from 1940 to present)
Nonseasonal component of average daily temperature	Physical climate risk	Copernicus Datastore (Dataset: ERA5 hourly data on single levels from 1940 to present)
Drought (Soil Moisture Anomaly index, negative part)	Physical climate risk	Global Drought Observatory
Flood (Soil Moisture Anomaly index, positive part)	Physical climate risk	Global Drought Observatory
Fire Weather Index	Physical climate risk	Copernicus Datastore (Dataset: Fire danger indicators for Europe from 1970 to 2098 derived from climate projections)
Log-returns of ETS carbon allowances	Transition climate risk	Refinitiv Datastream
Increments in EURIBOR rate	Debt servicing costs	Refinitiv Datastream
Increments EURIBOR rate slope (NSS β_1)	Debt servicing costs	Elaboration of EURIBOR rate data
Increments in EURIBOR rate convexity (NSS β_2)	Debt servicing costs	Elaboration of EURIBOR rate data
Increments in bond bid-ask spread	Bond liquidity	Refinitiv Datastream
Log-returns of local stock market index	Prevailing business climate	Refinitiv Datastream
Increments in VIX index	Global risk appetite	Refinitiv Datastream
Gross Domestic Product (GDP) %change	Health of the country's economy	Eurostat (Dataset: namq_10_gdp)
Industrial Production Index (IPI) %change	Health of the country's economy	Eurostat (Dataset: sts_esms)
Real Effective Exchange Rate (REER) %change	International competitiveness of the economy	Bruegel
Relative country debt size in Euro area %change	Debt liquidity	Eurostat (Dataset: gov_10q_ggfa)
Inflation Rate %change	Debt servicing costs	Eurostat (Dataset: PRC_HICP_MMOR)
Current Account balance %change	International competitiveness of the economy	Eurostat (Dataset: bop_c6_m)
Debt-to-GDP ratio %change	Country fiscal position	Eurostat (Dataset: gov_10q_ggdebt)
Financial Net Worth (FNW) %change	Country fiscal position	Eurostat (Dataset: gov_10q_ggfa)

Fig. 6 Temperature (°C)



5 Results

The results of the analyses enable us to identify which variables are significantly related to changes in bond spreads, and for which sovereign issuers. Sections 5.1 and 5.2 provide an overview of the results of the time-series and tail-dependence analyses, respectively, by country and with a special focus on the different behavior of green and non-green bonds. Section 6 then focuses on the implications of the results for financial stability: it investigates in greater detail the most relevant climate risk factors for each sovereign issuer, as emerging from the two types of analysis, and links the results to known climate change challenges having already arisen in each country.

5.1 Time series analysis

The first step of the time series analysis is the identification of the risk proxies to be used as exogenous regressors whenever multiple options are available and if, in order to avoid multicollinearity concerns, only one of them can be included. This is the case for drought risk, transition risk, and slope and convexity of the EURIBOR curves. In all these settings, models with each potential risk proxy are fit separately and then compared. Afterwards, the variable with the largest explanatory power is uniquely selected for the final model. More details about the selection process are reported in Appendix A.

Tables 37, 38, 40, 39, 41 summarise the number of statistically significant relationships of the spreads of each government with every exogenous regressor. The most significant regressors for Italian and German government bond spreads, in Tables 37 and 38, are changes in the EURIBOR rate, in the bid-ask spread, log-returns in the FTSE MIB index, and changes in the country's financial net worth. The signs of the coefficients are coherent with expectations: increases in the benchmark rate lead to a higher cost of debt servicing and lead to an increase in spreads, while increases in the financial net worth and log-returns of the local stock market index signal an increase in the creditworthiness of the country, thus reducing bond spreads. For French government bonds, changes in the DEBT-to-GDP ratio are also among the most relevant regressors. In line with Giordano et al. (2012), the average coefficient - as for the other countries - is negative. Dutch government spreads are also frequently linked to the industrial production index, with an increase in industrial production leading to a decrease in the spreads - again in line with the interpretation of this variable as an indicator of national economic well-being.

As for climate variables, they are reported in greater detail, such as bond average age, liquidity, and residual maturity, for each country in Tables 5, 6, 7, 8, and 9. The tables display the number (denoted as "Nr. of (S) bonds") of statistically significant relationships between its green and non-green bonds, on the one hand, and the climate risk proxies, on the other. They also show the average coefficient $\alpha_{b,j}$ of the significant bonds ("Avg. Coefficient (S)"). Additional consideration is given to the difference in the liquidity of the significant ("Avg. bid-ask (S)") and the non-significant ("Avg. bid-ask (NS)") bonds of each issuer, to their average age ("Avg. Age (S)" and "Avg. Age (NS)"), in years, and to differences in their residual maturities ("Avg. res. mat. (S)" and "Avg. res. mat. (NS)"), also in years. Due to a limitation in the data collection process, the ages are capped at a maximum of nine years (corresponding to the first observation in the sample). However, this has no impact on our considerations: our interest is directed to how much of the sample period (its entirety, versus only the last n years) is covered by the time series of each bond. Liquidity, age, and residual maturity affect the sensitivity of bond prices, so they are reported as potential explanations for the different degree of reactivity to physical risk proxies for significant and non-significant bonds. Residual maturity is a factor that we consider also in light of the findings in Bats et al. (2023), which reports a greater reactivity of bonds with longer-term maturities to climate variables.

The signs of the average coefficients should be interpreted as follows: a negative one indicates that the bond spreads tend to decrease when the size of the physical risk variable increases, meaning that the market seems to treat the bonds as hedging against physical risk. Their prices (and thus spreads) react as if they were positively affected by increases in the physical risk proxies. A zero average coefficient, or the absence of significant relationships, points to a the absence of correlation between the bond spreads and the climate variable at hand. A positive sign, instead, indicates that the bond spreads tend to increase, together with the perceived riskiness of the issuer, when the size of the physical risk variable increases.

In the case of French government bonds, summarized in Table 5, green and non-green bonds have a comparable relationship with climate risk proxies. For the variables with which non-green bonds have no or a very limited number of significant relationships (eastward wind, northward wind, drought, flood, and FWI), green bonds either also have no significant relationship, or, in the case of eastward wind, a slightly negative one. Average temperature is the climate risk proxy with which non-green bonds have the highest number of significant relationships, with a positive average coefficient. Again, green bonds behave very similarly to non-green ones.

As for the Netherlands, with results reported in Table 8, green and non-green bonds also have a comparable relationship with climate risk proxies. The number of significant relationships is zero or very low for non-green bonds, and the one outstanding green bond is unrelated to all variables except for one.

German government bonds, in Table 6, on the other hand, present a more divergent behavior of the two categories of bonds. For some risk factors, namely drought, flood and eastward wind, green and non-green bonds have similar proportions of significant relationships and same coefficient signs. For the three remaining factors, however, while traditional bonds have positive average coefficients (indicating an increase in their perceived riskiness, when the size of the physical risk variable increases), green bonds either have no significant relationship, or a negative one. In these cases, the market appears to be treating green bonds as hedges against physical risk: although they share the same issuer, they react as if they were unaffected, or positively affected, by increases in the physical risk proxies.

A similar and even more extreme situation happens for Italian green bonds: they are only significantly related to two climate variables, while the traditional bonds share a number of significant relationships with all risk proxies. The key details are summarised in Table 7.

Finally, Spanish government bonds show the greatest difference in behavior between green and non-green ones. As can be seen in Table 9, while traditional bonds have a number of significant relationships with all climate risk proxies, the one outstanding green bond is not significantly related to any of them.

The next section presents an analysis of the variance of the spreads, by fitting a GARCHX model to the residuals, in order to understand whether climate risk plays a role in the observed heteroskedasticity of the time series.

5.1.1 ARIMAX-GARCHX model fit

We next move onto the fit of ARIMAX-GARCHX models to the data, in order to evaluate the potential impact of climate risk factors on spread variance. The models are fit in R using the *rugarch* library. All exogenous regressors are included, as there is no motivation to justify the a priori exclusion of any of them. The results of the statistical significance of the lagged climate risk factors in the variance are reported in Tables 10, 11, 12, 13, and 14. We note that all coefficients are necessarily non-negative, due to the design of GARCHX models. We observe that, on average, a larger number of statistically significant relationships with the climate risk proxies emerges, for each country, than in the previous paragraph. This supports the hypothesis that climate risk contributes to the variance of the spreads and indicates that its impact is larger on their volatility than it is on their mean. The most important climate risk factors, by country, have a noticeable overlap with the ones determined in the ARIMAX analysis: temperature for France, wildfire risk for the Netherlands, drought, temperature, and

Table 5 FRANCE REPUBLIC OF (GOVERNMENT) ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Green bonds						
Avg. coefficient (S)	−0.0115	–	0.0111	–	–	–
Avg. age (S)	6.0877	–	6.0877	–	–	–
Avg. age (NS)	1.9452	4.0164	1.9452	4.0164	4.0164	4.0164
Avg. res. mat. (S)	16.3342	–	16.3342	–	–	–
Avg. res. mat. (NS)	21.3397	18.8370	21.3397	18.8370	18.8370	18.8370
Avg. bid-ask (S)	0.0021	–	0.0021	–	–	–
Avg. bid-ask (NS)	−0.0039	−0.0009	−0.0039	−0.0009	−0.0009	−0.0009
Nr. of (S) bonds	1	0	1	0	0	0
Tot. nr. of bonds	2	2	2	2	2	2
Non-Green bonds						
Avg. coefficient (S)	–	–	0.0159	–	−0.0167	−0.0213
Avg. age (S)	–	–	9.0685	–	9.0685	9.0685
Avg. age (NS)	9.0685	9.0685	9.0685	9.0685	9.0685	9.0685
Avg. res. mat. (S)	–	–	8.0093	–	2.9936	4.4103
Avg. res. mat. (NS)	13.8336	13.8336	15.9969	13.8336	14.5562	14.6902
Avg. bid-ask (S)	–	–	0.9176	–	0.1691	0.7207
Avg. bid-ask (NS)	1.1945	1.1945	1.2973	1.1945	1.2629	1.2376
Nr. of (S) bonds	0	0	13	0	3	4
Tot. nr. of bonds	48	48	48	48	48	48

Table 6 GERMANY FEDERAL REPUBLIC OF (GOVERNMENT) ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Green bonds						
Avg. coefficient (S)	0.1635	–	–	0.0237	−0.1098	−0.0571
Avg. age (S)	0.4795	–	–	2.4740	0.9849	2.3096
Avg. age (NS)	2.0171	1.7096	1.7096	1.5185	2.1927	1.5596
Avg. res. mat. (S)	4.6329	–	–	7.4685	6.5507	2.6192
Avg. res. mat. (NS)	11.5096	10.1342	10.1342	10.8007	12.5233	12.0130
Avg. bid-ask (S)	0.0008	–	–	0.0017	0.0010	0.0013
Avg. bid-ask (NS)	0.0030	0.0026	0.0026	0.0028	0.0036	0.0029
Nr. of (S) bonds	1	0	0	1	2	1
Tot. nr. of bonds	5	5	5	5	5	5
Non-Green bonds						
Avg. coefficient (S)	0.0117	0.0052	0.0105	0.0091	−0.0303	0.0097
Avg. age (S)	7.6616	7.3425	5.7292	7.0479	2.6274	5.1452
Avg. age (NS)	7.4634	7.5234	7.6546	7.5727	7.6346	7.7781
Avg. res. mat. (S)	11.9360	10.4226	10.2790	9.0616	2.6288	5.9421
Avg. res. mat. (NS)	8.6529	9.2090	9.2553	9.3759	9.5139	9.7284
Avg. bid-ask (S)	1.2255	0.7725	1.1221	0.6045	0.0392	0.4310
Avg. bid-ask (NS)	0.9377	1.0236	0.9870	1.0562	1.0231	1.0632
Nr. of (S) bonds	16	8	6	10	2	8
Tot. nr. of bonds	77	77	77	77	77	77

Table 7 ITALY REPUBLIC OF (GOVERNMENT) ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Green bonds						
Avg. coefficient (S)	0.0247	–	–	–	–	−0.0077
Avg. age (S)	0.4603	–	–	–	–	1.9699
Avg. age (NS)	1.9699	1.2151	1.2151	1.2151	1.2151	0.4603
Avg. res. mat. (S)	12.1781	–	–	–	–	22.1863
Avg. res. mat. (NS)	22.1863	17.1822	17.1822	17.1822	17.1822	12.1781
Avg. bid-ask (S)	−0.0166	–	–	–	–	0.0055
Avg. bid-ask (NS)	0.0055	−0.0055	−0.0055	−0.0055	−0.0055	−0.0166
Nr. of (S) bonds	1	0	0	0	0	1
Tot. nr. of bonds	2	2	2	2	2	2
Non-Green bonds						
Avg. coefficient (S)	−0.0544	0.0420	−0.0684	0.0885	−0.2139	−0.0247
Avg. age (S)	4.1692	3.5991	4.8178	4.9994	2.9384	2.0902
Avg. age (NS)	5.9869	6.1502	5.9783	6.0310	6.2552	6.1601
Avg. res. mat. (S)	11.2065	18.3657	8.7632	10.5667	13.7935	6.7454
Avg. res. mat. (NS)	10.8793	9.9678	11.1282	10.9642	10.5172	11.2237
Avg. bid-ask (S)	1.0411	1.9198	0.6704	0.6845	1.3711	0.0674
Avg. bid-ask (NS)	0.8868	0.7687	0.9212	0.9374	0.8339	0.9616
Nr. of (S) bonds	22	37	32	53	39	24
Tot. nr. of bonds	333	333	333	333	333	333

Table 8 NETHERLANDS KINGDOM OF THE (GOVERNMENT) ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Green bonds						
Avg. coefficient (S)	–	–	–	0.0887	–	–
Avg. age (S)	–	–	–	3.7589	–	–
Avg. age (NS)	3.7589	3.7589	3.7589	–	3.7589	3.7589
Avg. res. mat. (S)	–	–	–	16.8932	–	–
Avg. res. mat. (NS)	16.8932	16.8932	16.8932	–	16.8932	16.8932
Avg. bid-ask (S)	–	–	–	0.0026	–	–
Avg. bid-ask (NS)	0.0026	0.0026	0.0026	–	0.0026	0.0026
Nr. of (S) bonds	0	0	0	1	0	0
Tot. nr. of bonds	1	1	1	1	1	1
Non-Green bonds						
Avg. coefficient (S)	0.0173	0.0095	−0.0079	–	–	0.0323
Avg. age (S)	9.0685	9.0685	9.0685	–	–	9.0685
Avg. age (NS)	8.8185	8.8511	8.8412	8.8602	8.8602	8.8304
Avg. res. mat. (S)	11.1404	12.8904	45.3918	–	–	12.8904
Avg. res. mat. (NS)	15.2632	14.6493	11.7746	14.5760	14.5760	14.8168
Avg. bid-ask (S)	0.6875	0	1.0901	–	–	1.0905
Avg. bid-ask (NS)	0.6826	0.7131	0.6465	0.6834	0.6834	0.6253
Nr. of (S) bonds	4	1	2	0	0	3
Tot. nr. of bonds	24	24	24	24	24	24

Table 9 SPAIN KINGDOM OF (GOVERNMENT) ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Green bonds						
Avg. coefficient (S)	–	–	–	–	–	–
Avg. age (S)	–	–	–	–	–	–
Avg. age (NS)	1.4548	1.4548	1.4548	1.4548	1.4548	1.4548
Avg. res. mat. (S)	–	–	–	–	–	–
Avg. res. mat. (NS)	19.4329	19.4329	19.4329	19.4329	19.4329	19.4329
Avg. bid-ask (S)	–	–	–	–	–	–
Avg. bid-ask (NS)	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048
Nr. of (S) bonds	0	0	0	0	0	0
Tot. nr. of bonds	1	1	1	1	1	1
Non-Green bonds						
Avg. coefficient (S)	0.0282	0.0211	0.0123	−0.0026	0.0227	−0.0294
Avg. age (S)	4.6032	5.0450	4.8041	6.6855	4.8648	4.8280
Avg. age (NS)	6.4792	6.4399	6.7496	6.2559	6.6401	6.4714
Avg. res. mat. (S)	8.9279	6.2797	11.7803	4.6963	21.6318	3.6432
Avg. res. mat. (NS)	15.9909	16.2263	16.4256	17.5057	14.0784	16.5563
Avg. bid-ask (S)	0.0135	0.1004	0.0546	0.1524	0.3538	0.0271
Avg. bid-ask (NS)	0.5014	0.4937	0.5748	0.5219	0.4847	0.5037
Nr. of (S) bonds	12	12	32	24	26	13
Tot. nr. of bonds	147	147	147	147	147	147

flood for Italy and Spain. Interestingly, wildfire risk emerges as a new important risk factor for Germany. Overall, a lower proportion of green bonds exhibits a statistically significant relationship with climate risk proxies, compared to non-green ones. Further discussion is presented in Section 6.

In order to ensure the reliability of the inference based on the ARIMAX-GARCHX model, we perform a likelihood-ratio test. We compare this specification to the more parsimonious ARIMAX-GARCH model, for all countries. This is possible since the two models are nested. The results are presented in Table 15: the null hypothesis of the restricted model (ARIMAX-GARCH) providing an equivalent fit to the unrestricted one (ARIMAX-GARCHX) is rejected for a majority of the bonds in the sample, at the 5% significance level.

5.1.2 Model in-sample and out-of-sample goodness of fit

The in-sample and out-of-sample goodness of fit of the ARIMAX-GARCHX model are next assessed. Due to the large size of the sample, values are reported as aggregates. The aggregation is the same as the one used to present the previous results: by country and by bond type (green and non-green). In this section, the out-of-sample performance of the ARIMAX-GARCHX model is compared to that of a more standard, benchmark model: given the intrinsic difficulty of predicting financial quantities, forecast accuracy measures can be seen as relative values, which therefore become more meaningful when compared to those of alternative models. For this initial assessment, only one out-of-sample forecast window is selected, of length 5 days, i.e. one business week. This is done to evaluate the performance of the models over a short-term horizon that is not purely speculative. This time frame is longer than the standard two-business-day settlement period for bonds introduced in the 2014 EU Central Securities Depositories Regulation (CSDR), but enables for the evaluation of model performance over multiple days while avoiding potential confounding effects that could be introduced by a longer horizon. Section 5.1.3 will then explore model performance of the ARIMAX-GARCHX model over multiple forecast windows of differing lengths, to explicitly assess its use potential for short-term speculative purposes and long-term projections, and will evaluate the usefulness of climate risk factors in prediction.

The first goodness of fit measure measure is the Normalized Mean Absolute Error (NMAE). For each bond b, it equals the Mean Absolute Error (MAE) of the forecast spread increments, $\Delta\hat{s}_{b,t}$, divided by the range of the observed spread increments, $\max_t \Delta s_{b,t} - \min_t \Delta s_{b,t}$, i.e.

$$NMAE_b = \sum_{t=1}^{t_n} \frac{|\Delta\hat{s}_{b,t} - \Delta s_{b,t}|}{t_n} \cdot \frac{1}{\max_t \Delta s_{b,t} - \min_t \Delta s_{b,t}},$$

where $\Delta s_{b,t}$ is the observed spread increment at time t and t_n is the total number of observations. The normalization ensures the comparability of MAE values across bond time series, regardless of scale differences. Table 16 holds the in-sample values of NMAE, by country and by bond type. Overall, the quality of the model fit is rather satisfactory, with minima as low as 0.2% of the scale of the predicted variable,

Table 10 FRANCE REPUBLIC OF (GOVERNMENT) (GOVERNMENT), GARCHX regressors ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI	Carbon allow.
Green bonds							
Avg. coefficient (S)	–	–	0.1699	0.1540	0.0026	–	–
Avg. Age (S)	–	–	4.0164	4.0164	6.0877	–	–
Avg. Age (NS)	4.0164	4.0164	–	–	1.9452	4.0164	4.0164
Avg. res. mat. (S)	–	–	18.8370	18.8370	16.3342	–	–
Avg. res. mat. (NS)	18.8370	18.8370	–	–	21.3397	18.8370	18.8370
Avg. bid-ask (S)	–	–	−0.0009	−0.0009	0.0021	–	–
Avg. bid-ask (NS)	−0.0009	−0.0009	–	–	−0.0039	−0.0009	−0.0009
Nr. of (S) bonds	0	0	2	2	1	0	0
Tot. nr. of bonds	2	2	2	2	2	2	2
Non-green bonds							
Avg. coefficient (S)	0.0011	0.0008	0.1051	0.1336	0.0096	0.0176	0.0008
Avg. Age (S)	9.0685	9.0685	9.0685	9.0685	9.0685	9.0685	9.0685
Avg. Age (NS)	9.0685	9.0685	–	9.0685	9.0685	9.0685	9.0685
Avg. res. mat. (S)	12.5411	6.6616	13.0036	11.7656	10.3314	8.8637	11.1644
Avg. res. mat. (NS)	13.0510	13.3129	–	18.4199	14.9276	16.6035	13.0933
Avg. bid-ask (S)	1.2975	0.9189	1.1632	1.1998	1.0546	0.9792	1.2710
Avg. bid-ask (NS)	1.1494	1.1751	–	1.0031	1.2414	1.3231	1.1579
Nr. of (S) bonds	4	2	43	35	18	20	2
Tot. nr. of bonds	48	48	48	48	48	48	48

Table 11 GERMANY FEDERAL REPUBLIC OF (GOVERNMENT) (GOVERNMENT), GARCHX regressors ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI	Carbon allow.
Green bonds							
Avg. coefficient (S)	0.0043	0.0003	0.0849	0.3289	0.1033	–	0.0015
Avg. Age (S)	1.4904	1.7945	2.1927	2.0171	2.1927	–	2.3918
Avg. Age (NS)	1.7644	1.6884	–	–	–	1.7096	1.2548
Avg. res. mat. (S)	8.4685	27.4822	12.5233	11.5096	12.5233	–	5.0438
Avg. res. mat. (NS)	10.5507	5.7973	–	–	–	10.1342	13.5279
Avg. bid-ask (S)	0.0012	0.0077	0.0036	0.0030	0.0036	–	0.0015
Avg. bid-ask (NS)	0.0029	0.0013	–	–	–	0.0026	0.0032
Nr. of (S) bonds	1	2	5	5	5	0	4
Tot. nr. of bonds	5	5	5	5	5	5	5
Non-green bonds							
Avg. coefficient (S)	0	0.0033	0.0493	0.2606	0.1282	0.1325	0.0019
Avg. Age (S)	8.3425	4.5008	6.4550	4.9709	7.0691	7.3974	4.7877
Avg. Age (NS)	7.4935	7.7132	7.9516	8.1360	7.7677	7.6921	7.6534
Avg. res. mat. (S)	1.3507	4.1381	6.9309	3.9686	9.1170	7.9133	5.0486
Avg. res. mat. (NS)	9.4401	9.6960	10.3591	10.5171	9.4668	11.8232	9.5699
Avg. bid-ask (S)	0.5084	0.3290	0.5526	0.5105	1.0733	0.7651	0.3095
Avg. bid-ask (NS)	1.0040	1.0440	1.1870	1.1132	0.9518	1.4043	1.0352
Nr. of (S) bonds	1	5	23	13	29	49	4
Tot. nr. of bonds	77	77	77	77	77	77	77

Table 12 ITALY REPUBLIC OF (GOVERNMENT), GARCHX regressors ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI	Carbon allow.
Green bonds							
Avg. coefficient (S)	–	–	–	–	–	–	–
Avg. Age (S)	–	–	–	–	–	–	–
Avg. Age (NS)	1.9699	1.9699	1.9699	1.9699	1.9699	1.9699	1.9699
Avg. res. mat. (S)	–	–	–	–	–	–	–
Avg. res. mat. (NS)	22.1863	22.1863	22.1863	22.1863	22.1863	22.1863	22.1863
Avg. bid-ask (S)	–	–	–	–	–	–	–
Avg. bid-ask (NS)	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055
Nr. of (S) bonds	0	0	0	0	0	0	0
Tot. nr. of bonds	2	2	2	2	2	2	2
Non-green bonds							
Avg. coefficient (S)	0.0045	0.0908	0.0675	0.3343	0.0600	0.0815	0.0198
Avg. Age (S)	5.7587	4.6188	6.3586	6.3018	5.6167	5.8275	3.1762
Avg. Age (NS)	5.9315	6.3588	5.2086	7.4063	6.2949	6.5312	6.2100
Avg. res. mat. (S)	25.1279	12.2869	13.6579	11.6481	12.5687	14.0430	15.3735
Avg. res. mat. (NS)	9.0902	10.4930	6.3693	9.2691	9.7712	10.4574	10.4840
Avg. bid-ask (S)	2.9732	1.0489	1.3164	1.0270	1.1761	1.4947	1.6667
Avg. bid-ask (NS)	0.6446	0.8783	0.2597	0.5264	0.7364	0.7817	0.8356
Nr. of (S) bonds	38	80	203	280	141	88	32
Tot. nr. of bonds	333	333	333	333	333	333	333

Table 13 NETHERLANDS KINGDOM OF (GOVERNMENT), GARCHX regressors ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI	Carbon allow.
Green bonds							
Avg. coefficient (S)	–	–	0.0291	0.2166	0.0621	0.1052	–
Avg. Age (S)	–	–	3.7589	3.7589	3.7589	3.7589	–
Avg. Age (NS)	3.7589	3.7589	–	–	–	–	3.7589
Avg. res. mat. (S)	–	–	16.8932	16.8932	16.8932	16.8932	–
Avg. res. mat. (NS)	16.8932	16.8932	–	–	–	–	16.8932
Avg. bid-ask (S)	–	–	0.0026	0.0026	0.0026	0.0026	–
Avg. bid-ask (NS)	0.0026	0.0026	–	–	–	–	0.0026
Nr. of (S) bonds	0	0	1	1	1	1	0
Tot. nr. of bonds	1	1	1	1	1	1	1
Non-green bonds							
Avg. coefficient (S)	0.0002	0.0137	0.0316	0.0341	0.0103	0.0751	0.0119
Avg. Age (S)	9.0685	9.0685	8.6839	8.7837	9.0685	8.8304	8.9205
Avg. Age (NS)	8.8304	8.5685	9.0685	9.0051	8.8185	9.0685	8.8407
Avg. res. mat. (S)	40.3890	11.0440	12.3100	14.8897	11.5571	15.8174	3.0493
Avg. res. mat. (NS)	12.7697	20.5370	18.8912	15.8153	15.7136	8.3890	16.9897
Avg. bid-ask (S)	1.3982	0.6191	0.5146	0.7588	0.6643	0.6944	0.2164
Avg. bid-ask (NS)	0.6479	0.8355	0.9713	0.6089	0.7205	0.9100	0.7877
Nr. of (S) bonds	2	13	13	16	3	21	3
Tot. nr. of bonds	24	24	24	24	24	24	24

Table 14 SPAIN KINGDOM OF (GOVERNMENT), GARCHX regressors ($\alpha = 0.05$)

	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI	Carbon allow.
Green bonds							
Avg. coefficient (S)	0.0046	–	0.2326	–	0.0107	–	0.0288
Avg. Age (S)	1.4548	–	1.4548	–	1.4548	–	1.4548
Avg. Age (NS)	–	1.4548	–	1.4548	–	1.4548	–
Avg. res. mat. (S)	19.4329	–	19.4329	–	19.4329	–	19.4329
Avg. res. mat. (NS)	–	19.4329	–	19.4329	–	19.4329	–
Avg. bid-ask (S)	0.0048	–	0.0048	–	0.0048	–	0.0048
Avg. bid-ask (NS)	–	0.0048	–	0.0048	–	0.0048	–
Nr. of (S) bonds	1	0	1	0	1	0	1
Tot. nr. of bonds	1	1	1	1	1	1	1
Non-green bonds							
Avg. coefficient (S)	0.0204	0.0140	0.0995	0.2375	0.0607	0.0356	0.0105
Avg. Age (S)	6.6507	5.9483	6.3173	6.5250	6.4631	6.1782	5.3707
Avg. Age (NS)	5.9433	6.4218	6.4589	4.3288	5.8427	6.5920	6.7868
Avg. res. mat. (S)	10.1485	15.8073	15.8207	15.2117	15.2881	20.7388	14.3942
Avg. res. mat. (NS)	21.6752	15.4388	4.7377	40.3689	18.6918	11.1316	16.0670
Avg. bid-ask (S)	0.4110	0.6233	0.4778	0.4871	0.4930	0.5538	0.2669
Avg. bid-ask (NS)	0.5264	0.4220	−0.0003	−0.0007	0.2681	0.3974	0.5616
Nr. of (S) bonds	78	31	142	139	130	67	48
Tot. nr. of bonds	147	147	147	147	147	147	147

Table 15 Likelihood ratio test, ARIMAX-GARCH vs ARIMAX-GARCHX models

	Rejection rate of H_0
Green bonds	
France	100%
Germany	100%
Italy	100%
Netherlands	100%
Spain	100%
Non-green bonds	
France	72.1%
Germany	71.4%
Italy	85.2%
Netherlands	73.9%
Spain	90.4%

Table 16 In-sample Normalized Mean Absolute Error, ARIMAX model

	Min. value	Max. value	Median value	Std. dev.
Green bonds				
France	0.049	0.074	0.062	0.018
Germany	0.055	0.087	0.067	0.012
Italy	0.067	0.082	0.075	0.011
Netherlands	0.054	0.054	0.054	0
Spain	0.077	0.077	0.077	0
Non-green bonds				
France	0.011	0.059	0.038	0.014
Germany	0.002	0.084	0.043	0.015
Italy	0.009	0.105	0.043	0.019
Netherlands	0.005	0.044	0.036	0.012
Spain	0.002	0.088	0.045	0.017

and maxima of at most 10.5%. The values are generally lower for non-green bonds, indicating an overall better quality of the fit in their case. The zero values of the standard deviation occur for the countries which only have one green bond in the sample. Table 17 holds the out-of-sample values of the NMAE, for a forecast window of 5 days. The difference in the quality of the model fit between green and non-green bonds is amplified, and the non-green NMAE are uniformly lower. The results of a competing model are also reported, in order to provide a benchmark for a comparison in the quality of the fit. This benchmark model, of the OLS type with the Heteroskedasticity- and Autocorrelation-Consistent (HAC) estimator of the variance-covariance matrix, is illustrated at the beginning of Appendix A. The corresponding NMAE are reported in Table 18.

Table 17 Out-of-sample Normalized Mean Absolute Error, five-day forecast, ARIMAX model

	Min. value	Max. value	Median value	Std. dev.
Green bonds				
France	0.51094	0.51764	0.51429	0.0047405
Germany	0.41163	1.8315	0.6638	0.63846
Italy	0.51121	0.70623	0.60872	0.1379
Netherlands	0.27848	0.27848	0.27848	0
Spain	0.38757	0.38757	0.38757	0
Non-green bonds				
France	0.30326	2.3418	0.55951	0.38655
Germany	0.22521	2.0885	0.492	0.33154
Italy	0.2618	2.277	0.47628	0.28467
Netherlands	0.21945	0.8007	0.37407	0.14154
Spain	0.24708	2.1626	0.46298	0.21634

Table 18 Out-of-sample Normalized Mean Absolute Error, five-day forecast, benchmark model

	Min. value	Max. value	Median value	Std. dev.
Green bonds				
France	0.59059	0.68169	0.63614	0.06442
Germany	0.50761	2.3185	0.83957	0.75622
Italy	0.37778	0.88465	0.63121	0.35841
Netherlands	0.41858	0.41858	0.41858	0
Spain	0.53015	0.53015	0.53015	0
Non-green bonds				
France	0.27158	2.0656	0.57275	0.41595
Germany	0.13973	2.3902	0.47292	0.44951
Italy	0.15029	2.586	0.4933	0.34155
Netherlands	0.25939	0.91065	0.42916	0.17855
Spain	0.20987	2.0066	0.40013	0.3113

The second goodness of fit measure measure is the Normalized Root Mean Square Error (NRMSE). For each bond b, it equals the Root Mean Square Error (RMSE) of the forecast spread increments, $\Delta\hat{s}_{b,t}$, divided by the range of the observed spread increments, $\max_t \Delta s_{b,t} - \min_t \Delta s_{b,t}$, i.e.

$$NRMSE_b = \sqrt{\sum_{t=1}^{t_n} \frac{(\Delta\hat{s}_{b,t} - \Delta s_{b,t})^2}{t_n}} \cdot \frac{1}{\max_t \Delta s_{b,t} - \min_t \Delta s_{b,t}}.$$

Once again, the normalization ensures the comparability of values across bond time series, regardless of scale differences. The NRMSE is more sensitive to outliers than the NMAE, as larger deviations from forecast values are amplified by the second power. Table 19 holds the in-sample values of NRMSE, by country and by bond type. Overall, the quality of the model fit is satisfactory, with minima as low as 2% of the scale of the predicted variable, and maxima of at most 13%. The values are generally lower for non-green bonds, indicating an overall better quality of the fit in their case. The zero values of the standard deviation occur for the countries which only have one green bond in the sample. Table 20 holds the out-of-sample values of the NRMSE, for a forecast window of 5 days. The difference in the model fit between green and non-green bonds is again amplified in the case of their out-of-sample performance, as the non-green NRMSE are consistently lower. The results of the benchmark model are reported in Table 21. Overall, the out-of-sample NRMSEs and NMAEs are much higher than the in-sample ones, with median values ranging from 27% to 84%. Therefore, the model fit on the entire sample of observations does not lead to point estimates which are satisfactory enough for short-term speculations. In light of this result, Section 5.1.3 adopts a rolling-window cross-validation approach for a variety of time horizons to check, among other goals, for potential improvements in forecasting performance.

For both measures, what emerges in the out-of-sample cases is a generally better performance of the ARIMAX model. There are however some exceptions, in which the benchmark model displays a lower error measure. Closer inspection reveals that these involve cases in which a big proportion of bonds have optimal AR and MA orders equal to zero - meaning that the ARIMAX model collapses to a simple linear regression. The two models are therefore fitting the same parameters, for the mean component, with a different treatment of the variance of residuals (and of the error distribution, which is of the Student-t type in the ARIMAX case). The ARIMAX model introduces additional complexity by fitting a GARCH(X) model to the residual variance, and some numerical error arising from the fit of more parameters could explain its slightly worse performance in those cases than the benchmark, when forecasting the mean. The benchmark instead provides a fixed estimate of residual variance. The trade-off between model complexity and forecast error can lead to different choices, depending on the objective of the model user. If the interest is the ability to forecast the time-varying future variance of spread residuals, the ARIMAX-GARCH(X) model should be preferred, as its variance structure provides a method to forecast it, while this is not possible with the benchmark model. The benchmark model is only able to provide a constant, as an estimate of the homoskedastic variance. If the goal of the user is an in-sample correlation analysis, the ARIMAX-GARCH(X) model should be preferred in the presence of strong autocorrelation and/or moving-average components, as inference on coefficients derived from the benchmark model could be biased: HAC corrections are found to perform poorly in small samples with strong autocorrelation, as per Müller (2014). The benchmark model is instead a more efficient and parsimonious choice for forecasting, in cases of large samples and when weak AR and MA effects are present in the time series of data, and if variance prediction or inference is not of interest. It is generally less precise, but is the better choice in the absence of heteroskedasticity.

Table 19 In-sample Normalized Root Mean Square Error

	Min. value	Max. value	Median value	Std. dev.
Green bonds				
France	0.072	0.100	0.086	0.020
Germany	0.078	0.116	0.092	0.014
Italy	0.094	0.105	0.100	0.008
Netherlands	0.077	0.077	0.077	0
Spain	0.105	0.105	0.105	0
Non-green bonds				
France	0.019	0.083	0.055	0.018
Germany	0.015	0.111	0.064	0.019
Italy	0.022	0.134	0.063	0.022
Netherlands	0.020	0.062	0.053	0.013
Spain	0.022	0.114	0.066	0.020

Table 20 Out-of-sample Normalized Root Mean Square Error, five-day forecast, ARIMAX model

	Min. value	Max. value	Median value	Std. dev.
Green bonds				
France	0.5694	0.67457	0.62198	0.074368
Germany	0.41699	1.8509	0.71766	0.63575
Italy	0.51206	0.75739	0.63472	0.17347
Netherlands	0.31427	0.31427	0.31427	0
Spain	0.39835	0.39835	0.39835	0
Non-green bonds				
France	0.35037	2.4969	0.62533	0.43691
Germany	0.26934	2.4627	0.54472	0.37996
Italy	0.31518	2.6465	0.55993	0.29551
Netherlands	0.2483	0.85702	0.49529	0.16079
Spain	0.29922	2.2139	0.50414	0.22861

5.1.3 Model cross-validation

Given the high number of parameters in the model, we evaluate its predictive ability and address the risk of overfitting via a rolling-window cross-validation procedure. First, the accuracy of rolling-window predictions of the ARIMAX-GARCHX models is assessed, for a variety of forecast horizons. Then, the performance is compared to that of ARIMAX-GARCHX models without climate risk factors, to address their usefulness. Finally, the variability of regressor coefficients across windows is computed, in order to evaluate the stability of the relationships identified. It is worth pointing out that the real spread variance is an unobserved value, therefore this out-of-sample forecast accuracy analysis is restricted to the the ARIMAX portion of the model, for

Table 21 Out-of-sample Normalized Root Mean Square Error, five-day forecast, benchmark model

	Min. value	Max. value	Median value	Std. dev.
Green bonds				
France	0.67925	0.71517	0.69721	0.025403
Germany	0.50893	1.6365	0.98602	0.4648
Italy	0.38169	0.94851	0.6651	0.4008
Netherlands	0.42941	0.42941	0.42941	0
Spain	0.57688	0.57688	0.57688	0
Non-green bonds				
France	0.327	2.528	0.62723	0.47365
Germany	0.15154	2.5302	0.54335	0.47599
Italy	0.18368	2.6121	0.58038	0.32852
Netherlands	0.29667	1.0386	0.52585	0.23156
Spain	0.2844	2.117	0.46163	0.32507

which there exist realized observable values to contrast with predictions, and is not extended to the GARCHX part.

Compared to the forecast assessment in Section 5.1.2, the rolling window procedure could lead to an improved predictive accuracy, given that the model parameters are re-estimated on a subsection of observations that are closer in time to the values being predicted, and not on the entire sample. The length of the calibration window is chosen to be 2/3 of each available time series, instead of a fixed number of days, due to the uneven length of the time series of the different bonds. This choice ensures reliable estimator convergence for the shorter time series, while leading to faster computations for the longer time series than would be achieved with a uniformly short rolling window. Five forecast horizons are considered: 2, 6, 10, 45 and 100 days after the end of the rolling window for model calibration. The shorter forecast horizons are included to evaluate the potential usefulness of the model for speculative purposes, with short-term predictions, in light of the standard two-business-day settlement period for bonds introduced in the 2014 EU Central Securities Depositories Regulation (CSDR). The longer horizons are instead considered to evaluate model reliability for the purpose of scenario analysis.

The predictive performance of the ARIMAX model is tested twice: once *with* climate-related exogenous covariates, and once *without* them. In both cases, the forecast performance is assessed with the use of the Normalized Root Mean Squared Error (NRMSE) and of the Normalized Mean Absolute Error (NMAE).

The overall predictive performance of the ARIMAX-GARCHX model *with* climate covariates is improved with respect to Section 5.1.2. This confirms that calibration on a rolling-window basis proves more useful, for prediction, than calibration on the entire available time series. The results can be seen in Tables 23 and 24, for the different forecast horizons and for each country. As in Section 5.1.2, the errors are generally lower for non-green bonds, indicating an overall better quality of the fit in their case. We also note that the zero values of the standard deviation occur whenever there is only

Table 22 Number and features of bonds for which the inclusion of climate coefficients improves forecast, by country

	Italy	Germany	France	Spain	Netherlands
Green bonds					
Avg. age (C)	0.4603	–	6.0877	–	3.7589
Avg. age (NC)	1.9699	1.7096	1.9452	1.4548	–
Avg. residual mat. (C)	12.1781	–	16.3342	–	16.8932
Avg. residual mat. (NC)	22.1863	10.1342	21.3397	19.4329	–
Avg. bid-ask spread (C)	0.0166	–	0.0021	–	0.0026
Avg. bid-ask spread (NC)	0.0055	0.0026	0.0039	0.0048	–
Nr. of (C) bonds	1	0	1	0	1
Total nr. of bonds	2	5	2	1	1
Non-green bonds					
Avg. age (C)	5.0251	7.3706	9.0685	6.0353	8.8005
Avg. age (NC)	6.5401	7.5548	9.0685	6.5977	9.0051
Avg. residual mat. (C)	10.6948	8.5629	12.4155	16.1014	19.3610
Avg. residual mat. (NC)	11.0658	9.6246	14.0361	14.7725	2.9554
Avg. bid-ask spread (C)	0.1364	0.8183	1.0526	0.0597	0.0487
Avg. bid-ask spread (NC)	0.1641	0.8242	1.2798	0.1376	0.1195
Nr. of (C) bonds	148	21	6	71	17
Total nr. of bonds	333	77	48	147	24

one green bond in the sample. The model performance, although noticeably improved, is still not precise enough for speculative short-term forecasting, but the error measures remain stable and consistent also for the longer forecast windows, indicating that the model can be useful for projections and scenario analyses which stretch over extended time horizons. As for the comparison with the ARIMAX-GARCHX model *without* climate covariates, averaging over all bonds, the model without climate covariates usually performs better than the model which includes them, as can be seen in the slightly lower error measures reported in Tables 25 and 26. This aggregate result is not surprising, as the number of statistically significant relationships in the mean of the process, presented in Section 5.1, Tables 5, 9, usually concerns a minority of the outstanding bonds. There is however a substantial number of bonds for which the ARIMAX-GARCHX model with climate risk factors performs better, leading to lower forecast errors. Some descriptive statistics about these bonds, grouped by country and by greenness, are reported in Table 22. The bonds for which the ARIMAX-GARCHX model with climate risk factors leads to better forecasts are denoted as (C), while the others are denoted as (NC). The (C) bonds have, in most cases, the lower average age and the greater liquidity, in terms of lower bid-ask spreads. It is also worth noting that the number of (C) bonds is very comparable to the number of statistically significant relationships highlighted in-sample, in Section 5.1, Tables 5, 9, and is sometimes even higher. We finally point out that there are some German (C) green bonds, but they only exhibit a superior performance in the model *with* climate risk factors for a limited number of forecast horizons, making their case less reliable than for the other bonds. We therefore choose to exclude them from Table 22. The comparison of the goodness of fit measures of the ARIMAX-GARCHX model *with* climate risk factors and *without* them, for (C) bonds, are in Appendix C.

Finally, the stability of the model is assessed by evaluating the size and variability of the estimated coefficients across rolling windows. For each bond, and for each forecast window length, the average coefficients of the regressors are computed across estimation windows. Their standard deviation is also found, to measure the variability over time. Then, the bonds are aggregated by country and by type (green vs non-green) and the average of the coefficients and of the corresponding standard deviations are computed across bonds. Tables 67, 76 hold the results for all five forecast horizons. The standard deviations are overall rather low, highlighting stability in the value of the fitted coefficients. This supports the robustness of the model in identifying structural relationships.

5.2 Tail dependence analysis

The indices are grouped by computing, for every issuer, the average index value ("Avg. value") and the overall proportion ("% Sign.") of bond spreads having a level of non-parametric tail dependence falling into the corresponding 95% bootstrapped confidence interval. The non-parametric 0.05 and 0.95-quantile dependence indices are found and aggregated separately for green and non-green bonds. They are denoted as "Lower t.d." and "Upper t.d", respectively, in the tables below.

Whenever, in this section, we refer to climate variables or bond spreads, the quantities of interest involved in the calculations are the time series of the corresponding standardized residuals, obtained through the procedure detailed in Section 3.2. We do not specify it explicitly for the sake of legibility. Similarly, whenever we refer to the lower and upper tail dependence indices, we refer to the indices of non-parametric 0.05 and 0.95-quantile dependence, respectively, as defined in Section 3.2.

As for the interpretation of the results, a strictly positive index of lower tail dependence means that drops in the climate risk factors frequently happen together with drops in the bond spreads, which are situations in which the riskiness of the underlying bonds decreases. Conversely, a strictly positive index of upper tail dependence points to simultaneity between spikes in the climate risk factors and spikes in the bond spreads, which imply an increase in the riskiness of the underlying bond that is priced by the market.

Tables 27, 31 hold the non-parametric tail dependence indices of Dutch, German, French, Italian, and Spanish government bonds.

Interestingly, green bonds mostly display lower proportions and lower average values of significant tail dependence indices than non-green ones with the climate risk proxies, for all countries except for France and the Netherlands. This division between countries, based on green bond behavior, is identical to the one that emerged in Section 5.1. This is coherent with an interpretation that the market reactions to climate risk, for Germany, Italy, and Spain, embed a preference for green bonds over

Table 23 Rolling window NRMSE values, ARIMAX model with climate regressors

Forecast horizon (days)	2	6	10	45	100
France, green bonds					
Median value	0.13572	0.13604	0.13616	0.13610	0.13606
Min. value	0.11086	0.11105	0.11097	0.11059	0.11165
Max. value	0.16058	0.16103	0.16135	0.16161	0.16047
Std. dev.	0.03516	0.03534	0.03562	0.03608	0.03452
France, non-green bonds					
Median value	0.07937	0.07937	0.07908	0.07891	0.07896
Min. value	0.06491	0.06496	0.06490	0.06520	0.06483
Max. value	0.12245	0.12198	0.12194	0.12203	0.12265
Std. dev.	0.01834	0.01820	0.01823	0.01814	0.01843
Germany, green bonds					
Median value	0.15568	0.15689	0.16076	0.15630	0.14937
Min. value	0.14312	0.14298	0.14316	0.14393	0.14453
Max. value	0.21141	0.23640	0.25019	0.26890	0.27409
Std. dev.	0.02750	0.03820	0.04444	0.05214	0.05508
Germany, non-green bonds					
Median value	0.10149	0.10151	0.10156	0.10184	0.10330
Min. value	0.03064	0.03064	0.03063	0.03066	0.03071
Max. value	0.22365	0.23097	0.19881	0.20699	0.21694
Std. dev.	0.02989	0.03029	0.02875	0.03013	0.03255
Italy, green bonds					
Median value	0.17149	0.17419	0.17645	0.16895	0.16920
Min. value	0.14952	0.15110	0.15193	0.15271	0.15320
Max. value	0.19347	0.19729	0.20097	0.18520	0.18520
Std. dev.	0.03107	0.03266	0.03467	0.02297	0.02262
Italy, non-green bonds					
Median value	0.10057	0.10101	0.10098	0.10305	0.10529
Min. value	0.04041	0.04042	0.04034	0.04210	0.04237
Max. value	0.62278	0.75274	0.84872	0.56228	0.89214
Std. dev.	0.07287	0.09116	0.09777	0.08221	0.10242
Netherlands, green bonds					
Median value	0.13136	0.13164	0.13173	0.13536	0.13821
Min. value	0.13136	0.13164	0.13173	0.13536	0.13821
Max. value	0.13136	0.13164	0.13173	0.13536	0.13821
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Netherlands, non-green bonds					
Median value	0.07963	0.07945	0.07950	0.07964	0.07977
Min. value	0.03147	0.03147	0.03147	0.03147	0.03147
Max. value	0.11708	0.11679	0.11695	0.11731	0.11690
Std. dev.	0.01760	0.01755	0.01756	0.01765	0.01764

Table 23 continued

Forecast horizon (days)	2	6	10	45	100
Spain, green bonds					
Median value	0.17450	0.17932	0.18069	0.17029	0.16648
Min. value	0.17450	0.17932	0.18069	0.17029	0.16648
Max. value	0.17450	0.17932	0.18069	0.17029	0.16648
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Spain, non-green bonds					
Median value	0.11214	0.11332	0.11145	0.11235	0.11444
Min. value	0.06044	0.06007	0.05982	0.06138	0.06059
Max. value	0.99041	0.80742	0.92875	0.67732	0.47537
Std. dev.	0.09633	0.07663	0.10506	0.06574	0.05583

non-green ones, while, for France and the Netherlands, no such preference seems to emerge.

In fact, as can be seen in Table 27, the percentage of significant tail dependence relationships is often even higher, at least in the upper tail, for green bonds than for non-green ones. French green bonds, shown in Table 28, behave similarly to their non-green counterparts, although they show a decrease in the proportion of significant indices with respect to some risk indicators.

The opposite is true for Spanish government green bonds, which, out of all countries, have the lowest amount of tail dependence with the proposed risk factors, compared to their non-green counterparts. However, Table 29 shows that they still co-move significantly, in the upper tail, with three proxies in particular: the non-seasonal component of eastward wind, the fire weater index, and the non-seasonal component of average daily temperature.

As for German government green bonds, summarized in Table 30, they have lower proportions of significant tail dependence relationships than non-green ones. In particular, while non-green bonds have equal levels of upper and lower tail dependence with some risk factors, or a stronger upper one, the green bonds frequently display an asymmetric tail relationship, with stronger levels of lower tail dependence. We recall that lower tail dependence implies that declines in climate risk factors happen together with drops in bond spreads. These are moments in which the overall riskiness of the underlying bonds decreases.

Finally, Italian government green bonds have noticeably lower proportions of significant tail dependence relationships with the risk proxies than the non-green ones.

We put forth a few potential explanations for the difference between the tail dependence exhibited by German, Italian, and Spanish green bonds, on one side, and those of France and the Netherlands, on the other. More precisely, we are interested in understanding why the former three mostly display lower levels of tail dependence than their non-green analogues, while the latter two behave similarly to their traditional counterparts.

Table 24 Rolling window NMAE values, ARIMAX model with climate regressors

Forecast horizon (days)	2	6	10	45	100
France, green bonds					
Median value	0.10084	0.10098	0.10098	0.10143	0.10099
Min. value	0.07885	0.07903	0.07895	0.07923	0.07962
Max. value	0.12284	0.12294	0.12301	0.12362	0.12237
Std. dev.	0.03111	0.03105	0.03115	0.03139	0.03023
France, non-green bonds					
Median value	0.05271	0.05268	0.05270	0.05280	0.05289
Min. value	0.03893	0.03902	0.03905	0.03943	0.03914
Max. value	0.08826	0.08813	0.08829	0.08838	0.08884
Std. dev.	0.01575	0.01571	0.01574	0.01569	0.01591
Germany, green bonds					
Median value	0.12028	0.12196	0.12577	0.12067	0.11839
Min. value	0.10706	0.10647	0.10659	0.10699	0.10758
Max. value	0.14685	0.16337	0.18738	0.21318	0.22276
Std. dev.	0.01579	0.02288	0.03314	0.04394	0.04818
Germany, non-green bonds					
Median value	0.06945	0.06945	0.06959	0.06970	0.06985
Min. value	0.00291	0.00293	0.00291	0.00300	0.00313
Max. value	0.14457	0.14878	0.13975	0.14029	0.14822
Std. dev.	0.02326	0.02349	0.02328	0.02422	0.02565
Italy, green bonds					
Median value	0.12614	0.13117	0.12688	0.12128	0.12227
Min. value	0.11517	0.11716	0.11858	0.11753	0.11950
Max. value	0.13712	0.14517	0.13519	0.12503	0.12503
Std. dev.	0.01552	0.01981	0.01175	0.00530	0.00391
Italy, non-green bonds					
Median value	0.06989	0.07001	0.07019	0.07109	0.07294
Min. value	0.02085	0.02089	0.02091	0.02216	0.02234
Max. value	0.37642	0.36259	0.42694	0.44287	0.44287
Std. dev.	0.04573	0.04659	0.04778	0.05039	0.04972
Netherlands, green bonds					
Median value	0.09937	0.09949	0.10070	0.10284	0.10519
Min. value	0.09937	0.09949	0.10070	0.10284	0.10519
Max. value	0.09937	0.09949	0.10070	0.10284	0.10519
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Netherlands, non-green bonds					
Median value	0.05335	0.05327	0.05330	0.05351	0.05333
Min. value	0.00858	0.00858	0.00857	0.00858	0.00858
Max. value	0.08431	0.08415	0.08433	0.08439	0.08422
Std. dev.	0.01597	0.01592	0.01598	0.01605	0.01600

Table 24 continued

Forecast horizon (days)	2	6	10	45	100
Spain, green bonds					
Median value	0.13714	0.14905	0.14653	0.12626	0.12405
Min. value	0.13714	0.14905	0.14653	0.12626	0.12405
Max. value	0.13714	0.14905	0.14653	0.12626	0.12405
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Spain, non-green bonds					
Median value	0.07898	0.08028	0.08003	0.07959	0.08073
Min. value	0.03810	0.03825	0.03840	0.03982	0.03902
Max. value	0.21010	0.24612	0.21298	0.27230	0.19353
Std. dev.	0.02365	0.02550	0.02445	0.02729	0.02405

First of all, we observe that the average age (as of the last day of the analysis, 27^{th} February 2023) of the French and Dutch green government bonds is higher than that of the other three countries. As can be seen in Table 32, it is 4.01 years for the French ones and 3.77 for the Dutch, while the average age of the German ones is 1.70 years, of the Spanish 1.45, and of the Italian 1.21 years, the lowest of all. Since the tail dependence is computed as a proportion of the sample size, a larger number of observations does not automatically lead to a higher level of tail dependence. However, the shorter time window covered by the latter three countries could exclude a proportionally higher number of extreme whether events that impacted the financial markets in the previous years, which would instead have affected the tail dependence of the French and Dutch bonds.

Alternatively, or additionally, differences in the issue size of the green bonds might provide some insight into their degree of connection with external factors, relative to non-green government bonds. The green bonds of the two groups of countries receive a different treatment on the part of the market, with Dutch and French bond spreads behaving comparably to their traditional counterparts, while German, Italian, and Spanish government bonds are comparatively less impacted by extreme events. Table 36 holds information about the issue size of each government green bond and about the total amount of sovereign debt outstanding at the end of the year ("EoY") of its issuance. Table 32 displays those values aggregated by country. We notice that the issue sizes of Dutch and French green government bonds represent the greatest proportion over the country's total debt, compared to the other countries. This could explain why they are treated by the market more similarly to traditional bonds, as their level of relative scarcity is lower. On the other hand, Spanish and Italian green bonds, in particular, are up to eight time scarcer than they are, representing less than 1% of the total outstanding debt of the respective countries. An additional element in support of this interpretation lies in the behavior of German green government bonds. They show lower levels of tail dependence than their non-green counterparts, but the difference is not as marked as it is for Italy and Spain. Coherently with this "middle-of-the-road" position, we observe that their total relative issue size is proportionally lower than

Table 25 Rolling window NRMSE values, ARIMAX model without climate regressors

Forecast horizon (days)	2	6	10	45	100
France, green bonds					
Median value	0.13511	0.13583	0.13475	0.13474	0.13578
Min. value	0.11095	0.11109	0.11072	0.11035	0.11158
Max. value	0.15928	0.16057	0.15878	0.15912	0.15998
Std. dev.	0.03417	0.03499	0.03399	0.03448	0.03423
France, non-green bonds					
Median value	0.07904	0.07906	0.07881	0.07872	0.07878
Min. value	0.06482	0.06482	0.06476	0.06493	0.06463
Max. value	0.12239	0.12193	0.12189	0.12194	0.12259
Std. dev.	0.01834	0.01820	0.01824	0.01813	0.01842
Germany, green bonds					
Median value	0.15363	0.15727	0.15733	0.15560	0.14748
Min. value	0.14299	0.14277	0.14315	0.14365	0.14409
Max. value	0.20692	0.21867	0.22309	0.19453	0.20080
Std. dev.	0.02652	0.03131	0.03307	0.02097	0.02427
Germany, non-green bonds					
Median value	0.10135	0.10133	0.10128	0.10123	0.10134
Min. value	0.03063	0.03063	0.03064	0.03065	0.03067
Max. value	0.21602	0.22443	0.18391	0.23734	0.24482
Std. dev.	0.02970	0.03025	0.02793	0.03075	0.03128
Italy, green bonds					
Median value	0.19071	0.18331	0.17923	0.18394	0.18375
Min. value	0.14873	0.14931	0.14946	0.15000	0.14961
Max. value	0.23270	0.21732	0.20900	0.21789	0.21789
Std. dev.	0.05938	0.04809	0.04210	0.04801	0.04828
Italy, non-green bonds					
Median value	0.09999	0.10042	0.10060	0.10030	0.10117
Min. value	0.04039	0.04040	0.04027	0.04046	0.04038
Max. value	0.44381	0.76288	0.67406	1.58360	1.58360
Std. dev.	0.06281	0.07403	0.07957	0.10115	0.11677
Netherlands, green bonds					
Median value	0.13168	0.13051	0.13020	0.13888	0.14100
Min. value	0.13168	0.13051	0.13020	0.13888	0.14100
Max. value	0.13168	0.13051	0.13020	0.13888	0.14100
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Netherlands, non-green bonds					
Median value	0.07942	0.07914	0.07928	0.07946	0.07928
Min. value	0.03147	0.03147	0.03148	0.03147	0.03147
Max. value	0.11692	0.11666	0.11679	0.11718	0.11678
Std. dev.	0.01757	0.01752	0.01753	0.01763	0.01760

Table 25 continued

Forecast horizon (days)	2	6	10	45	100
Spain, green bonds					
Median value	0.16423	0.17366	0.17131	0.16122	0.16233
Min. value	0.16423	0.17366	0.17131	0.16122	0.16233
Max. value	0.16423	0.17366	0.17131	0.16122	0.16233
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Spain, non-green bonds					
Median value	0.11071	0.11050	0.11039	0.11103	0.11153
Min. value	0.05993	0.06016	0.06014	0.06031	0.06046
Max. value	0.79006	0.79016	0.91675	0.60192	0.22690
Std. dev.	0.07202	0.06203	0.07137	0.04750	0.02758

that of the French and the Dutch, but substantially higher than that of the Spanish and the Italian. Finally, the condition of Spanish green government bonds, which have the greatest reduction of all countries in their tail dependence compared to the non-green ones, could be tied to their relative scarcity. They only represent 0.507% of the total government debt, which is the lowest proportion of all.

This explanation would support the interpretation that there is a preference for green bonds, enhanced by their relative scarcity, which renders their price, YTM, and spread less reactive than that of the non-green ones by the same issuer. This is in alignment with the preliminary analysis in Martiradonna et al. (2023) showed that the green-bond indices were less volatile than all others, including the traditional corporate bond index Bloomberg Barclays Global Aggregate Total Return Index (BBBOND), and the asset allocation portion of that analysis found that the optimal weights of all risk-reducing strategies gave a preference to the green-bond indices over the corporate ones.

Additionally, in Section 5.1 we found that, for some issuers, green bonds behaved differently than non-green ones and historically benefited, in terms of a decreased spreads, from increases in the climate risk factors, or had no dependence at all with them. On the other hand, the non-green counterparts were negatively affected, through an increase in their spread, by the same factors.

5.3 Linking green debt scarcity to climate risk

In order to further explore the link between the co-movement of green bond spreads and climate risk factors, on the one hand, and their relative scarcity, on the other, we perform one final empirical analysis. We perform K-means clustering of the green debt of the five sovereign issuers in this study. The clustering is based on a total of eight *features*: relative scarcity, measured as the total green debt issue size divided by oustanding debt, and its link with each of the seven climate risk proxies. The link is represented, for each climate variable, by the product of the average value of the corresponding upper tail dependence coefficient and the percentage of bonds for which that coefficient is statistically significant. These quantities are taken from Tables 27,

Table 26 Rolling window NMAE values, ARIMAX model without climate regressors

Forecast horizon (days)	2	6	10	45	100
France, green bonds					
Median value	0.10055	0.10137	0.10059	0.10058	0.10077
Min. value	0.07916	0.07909	0.07906	0.07900	0.07986
Max. value	0.12194	0.12364	0.12211	0.12217	0.12169
Std. dev.	0.03025	0.03150	0.03044	0.03052	0.02958
France, non-green bonds					
Median value	0.05266	0.05262	0.05263	0.05270	0.05283
Min. value	0.03886	0.03892	0.03894	0.03913	0.03887
Max. value	0.08822	0.08807	0.08823	0.08826	0.08869
Std. dev.	0.01578	0.01574	0.01577	0.01572	0.01592
Germany, green bonds					
Median value	0.11716	0.11934	0.12170	0.11856	0.11727
Min. value	0.10594	0.10596	0.10432	0.10659	0.10700
Max. value	0.13392	0.14700	0.15538	0.13693	0.14472
Std. dev.	0.01207	0.01690	0.02049	0.01273	0.01563
Germany, non-green bonds					
Median value	0.06931	0.06926	0.06918	0.06921	0.06958
Min. value	0.00289	0.00289	0.00289	0.00289	0.00290
Max. value	0.14088	0.14372	0.13010	0.17987	0.20147
Std. dev.	0.02341	0.02364	0.02250	0.02487	0.02632
Italy, green bonds					
Median value	0.13730	0.13706	0.13051	0.13261	0.13276
Min. value	0.11359	0.11493	0.11509	0.11412	0.11441
Max. value	0.16101	0.15919	0.14592	0.15110	0.15110
Std. dev.	0.03353	0.03130	0.02180	0.02615	0.02594
Italy, non-green bonds					
Median value	0.06948	0.06964	0.06976	0.07020	0.07066
Min. value	0.02079	0.02080	0.02079	0.02086	0.02083
Max. value	0.38305	0.41614	0.45275	1.53903	1.53903
Std. dev.	0.04581	0.04727	0.04962	0.09113	0.09143
Netherlands, green bonds					
Median value	0.09946	0.09858	0.09961	0.10659	0.10957
Min. value	0.09946	0.09858	0.09961	0.10659	0.10957
Max. value	0.09946	0.09858	0.09961	0.10659	0.10957
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Netherlands, non-green bonds					
Median value	0.05328	0.05322	0.05331	0.05340	0.05331
Min. value	0.00857	0.00857	0.00857	0.00857	0.00857
Max. value	0.08418	0.08404	0.08421	0.08429	0.08412
Std. dev.	0.01594	0.01591	0.01595	0.01600	0.01598

Table 26 continued

Forecast horizon (days)	2	6	10	45	100
Spain, green bonds					
Median value	0.12923	0.13902	0.13730	0.12258	0.12314
Min. value	0.12923	0.13902	0.13730	0.12258	0.12314
Max. value	0.12923	0.13902	0.13730	0.12258	0.12314
Std. dev.	0.00000	0.00000	0.00000	0.00000	0.00000
Spain, non-green bonds					
Median value	0.07858	0.07840	0.07844	0.07879	0.07880
Min. value	0.03788	0.03823	0.03849	0.03896	0.03892
Max. value	0.15434	0.15055	0.15934	0.45953	0.17536
Std. dev.	0.02049	0.02071	0.02069	0.03756	0.02231

Table 27 Tail dependence of Dutch bond spreads

		Green bonds		Non-green bonds	
		Upper t.d.	Lower t.d.	Upper t.d.	Lower t.d.
Eastw. wind	Avg. value	0.021	0.041	0.042	0.041
	% Sign.	1.000	1.000	0.792	0.917
Northw. wind	Avg. value	0.062	0.000	0.067	0.042
	% Sign.	1.000	0.000	0.750	1.000
Drought	Avg. value	0.062	0.062	0.065	0.053
	% Sign.	1.000	1.000	0.875	1.000
FWI	Avg. value	0.021	0.062	0.053	0.039
	% Sign.	1.000	1.000	0.958	0.958
Avg. temp	Avg. value	0.041	0.062	0.062	0.038
	% Sign.	1.000	1.000	0.958	0.917
Flood	Avg. value	0.103	0.082	0.058	0.060
	% Sign.	1.000	1.000	1.000	0.958
Carbon allow.	Avg. value	0.041	0.000	0.050	0.066
	% Sign.	1.000	0.000	0.958	0.667

28, 29, 30, and 31. The focus is on the upper tail dependence coefficient, as it is representative of negative scenarios, indicated by simultaneous realizations of high climate risk and high credit risk. The relative scarcity of green debt is instead taken from Table 32. The goal of k-means clustering is to find patters between the features of each country's green debt, creating subgroups which minimize the within-cluster sum of squared distances. If there is indeed a link between green debt scarcity and a lower connection with climate risk, the expected result is a division of countries in clusters which mirror the groupings observed in the previous paragraphs. The eight features used in the study are standardized before k-means clustering is performed, so that the relative weight of each one is the same. The number of clusters k is selected

Table 28 Tail dependence of French bond spreads

		Green bonds		Non-green bonds	
		Upper t.d.	Lower t.d.	Upper t.d.	Lower t.d.
Eastw. wind	Avg. value	0.039	0.051	0.043	0.050
	% Sign.	1.000	0.500	0.917	0.979
Northw. wind	Avg. value	0.033	0.085	0.054	0.045
	% Sign.	1.000	1.000	0.979	1.000
Drought	Avg. value	0.063	0.078	0.043	0.067
	% Sign.	0.500	1.000	0.958	0.833
FWI	Avg. value	0.058	0.038	0.057	0.045
	% Sign.	1.000	0.500	0.979	1.000
Avg. temp	Avg. value	0.084	0.025	0.075	0.034
	% Sign.	1.000	0.500	0.708	0.750
Flood	Avg. value	0.092	0.063	0.034	0.071
	% Sign.	1.000	0.500	0.854	0.771
Carbon allow.	Avg. value	0.080	0.089	0.034	0.072
	% Sign.	0.500	0.500	0.688	0.812

Table 29 Tail dependence of Spanish bond spreads

		Green bonds		Non-green bonds	
		Upper t.d.	Lower t.d.	Upper t.d.	Lower t.d.
Eastw. wind	Avg. value	0.053	0.106	0.047	0.054
	% Sign.	1.000	1.000	0.855	0.931
Northw. wind	Avg. value	0.000	0.053	0.052	0.042
	% Sign.	0.000	1.000	0.828	0.814
Drought	Avg. value	0.000	0.000	0.059	0.043
	% Sign.	0.000	0.000	0.917	0.828
FWI	Avg. value	0.106	0.106	0.054	0.062
	% Sign.	1.000	1.000	0.917	0.903
Avg. temp	Avg. value	0.053	0.053	0.056	0.044
	% Sign.	1.000	1.000	0.931	0.910
Flood	Avg. value	0.000	0.000	0.062	0.043
	% Sign.	0.000	0.000	0.897	0.828
Carbon allow.	Avg. value	0.000	0.000	0.036	0.065
	% Sign.	0.000	0.000	0.800	0.662

Table 30 Tail dependence of German bond spreads

		Green bonds		Non-green bonds	
		Upper t.d.	Lower t.d.	Upper t.d.	Lower t.d.
Eastw. wind	Avg. value	0.037	0.085	0.045	0.052
	% Sign.	0.400	0.800	0.947	0.882
Northw. wind	Avg. value	0.050	0.033	0.044	0.041
	% Sign.	0.600	0.200	0.921	0.908
Drought	Avg. value	0.091	0.050	0.041	0.047
	% Sign.	0.800	0.600	0.855	0.921
FWI	Avg. value	0.047	0.080	0.059	0.050
	% Sign.	0.600	0.800	0.921	0.921
Avg. temp	Avg. value	0.057	0.071	0.050	0.045
	% Sign.	0.600	0.600	0.961	0.961
Flood	Avg. value	0.057	0.094	0.058	0.052
	% Sign.	0.600	0.800	0.868	0.882
Carbon allow.	Avg. value	0.067	0.087	0.050	0.075
	% Sign.	0.600	0.200	0.947	0.526

Table 31 Tail dependence of Italian bond spreads

		Green bonds		Non-green bonds	
		Upper t.d.	Lower t.d.	Upper t.d.	Lower t.d.
Eastw. wind	Avg. value	0.000	0.039	0.059	0.060
	% Sign.	0.000	0.500	0.804	0.933
Northw. wind	Avg. value	0.039	0.000	0.041	0.060
	% Sign.	0.500	0.000	0.748	0.822
Drought	Avg. value	0.000	0.039	0.047	0.053
	% Sign.	0.000	0.500	0.831	0.877
FWI	Avg. value	0.039	0.039	0.061	0.052
	% Sign.	0.500	0.500	0.868	0.822
Avg. temp	Avg. value	0.039	0.000	0.051	0.061
	% Sign.	0.500	0.000	0.834	0.847
Flood	Avg. value	0.000	0.000	0.052	0.044
	% Sign.	0.000	0.000	0.874	0.804
Carbon allow.	Avg. value	0.039	0.078	0.034	0.069
	% Sign.	0.500	0.500	0.663	0.767

Table 32 Total relative issue size and average age of green government bonds

Country	Total issue size/ oustanding debt	Avg. age in years, as of 27/02/2023
France	1.957%	4.01
Netherlands	3.974%	3.77
Germany	1.472%	1.70
Spain	0.507%	1.45
Italy	0.721%	1.21

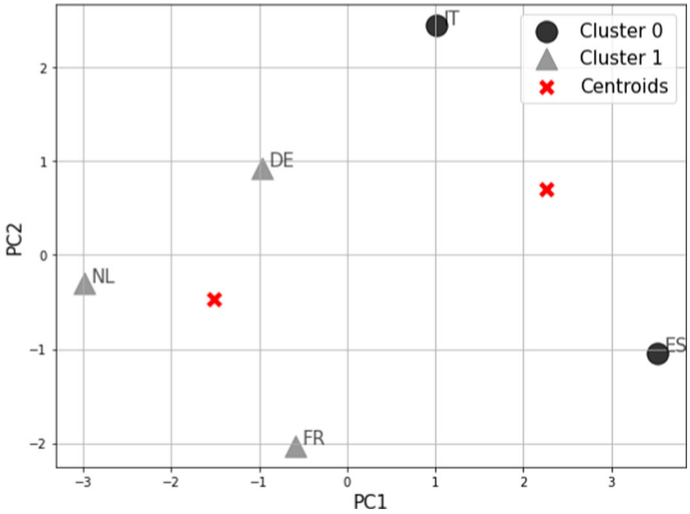


Fig. 7 Cluster assignments on plot of PCA of size 2

as the one which maximizes the silhouette score and is found to be equal to 2, as per Table 34.

The classification that emerges from k-means clustering is in fact the same that appeared from the initial inspection of the results: Italy and Spain are placed in cluster 0, while France and the Netherlands are placed in cluster 1. German green bonds, which in the previous sections we had evaluated to be in an intermediate position with respect to the two groups, are placed in cluster 1, together with France and the Netherlands. Interestingly, however, further insight can be provided by overlaying the (appropriately projected) cluster assignments on a plot of a Principal Component Analysis (PCA) of size 2, as is done in Figure 7. This enables us to visualize in a two-dimensional space the eight-dimensional features of each green bond that were used for clustering. The space is representative of the two uncorrelated components ("PC1" and "PC2") which capture the largest proportion of data variance. We see that, in this space, the position of German green bonds indeed falls in the middle between the two groups, but closer to cluster 1 than to cluster 0.

In Table 33, we report the mean values of each feature, by cluster. A clear pattern emerges, with cluster 0 having lower values than cluster 1 in almost all cases.

Table 33 Mean value of each feature, by cluster, green debt

Cluster	0	1
Eastw. wind	0.0265	0.0249
Northw. wind	0.0098	0.0417
Drought	0	0.0554
FWI	0.0628	0.0357
Avg. temp	0.0363	0.0531
Flood	0	0.0764
Carbon allow.	0.0098	0.0404
Rel. issue size	0.0061	0.0247

Table 34 Silhouette score of K-means clustering for different k

k	Silhouette score (green debt)	Silhouette score (non-green debt)
2	0.211	0.177
3	0.126	0.071
4	0.026	0.069

One final check is made. The clustering analysis of green bonds supports the presence of a link between the relative scarcity of green debt and its lower comovement with climate risk. This however implies that such link should not be present in the less scarce case of non-green debt. If our hypothesis is correct, we would therefore expect a more uniform picture to emerge, in terms of groups, when performing k-means clustering based on non-green debt features. More precisely, we would expect differences in the relative size of outstanding non-green debt to no longer be aligned with differences in its relationship with climate risk, leading to a different cluster composition than before. This is in fact what happens, after performing k-means clustering with $k = 2$ (chosen based on Table 34). First of all, the optimal division assigns all countries except for one to the same cluster: France, Germany, Spain, and Italy are assigned to cluster 1, while only the Netherlands are assigned to cluster 0. Secondly, the two clusters are more similar than in the green case. In fact, differences in mean feature values across clusters, reported in Table 35, are much less pronounced than for green debt, reported in Table 33.

6 Discussion

Multiple considerations emerge from this study, regarding the factors of interest for an effective management of climate risk, for the purpose of enhancing the stability of the financial system. We can observe differences in their geographical distribution across countries, as well as differences between their impact on average spread variations (as exogenous regressors of the ARIMAX models) and their level of tail dependence.

When analyzing in greater detail the results of the ARIMAX models, the most impactful risk factors, in terms of risk management considerations, are those which

Table 35 Mean value of each feature, by cluster, non-green debt

Cluster	0	1
Eastw. wind	0.0333	0.0424
Northw. wind	0.0503	0.0418
Drought	0.0569	0.0424
FWI	0.0508	0.0532
Avg. temp	0.0594	0.0490
Flood	0.0580	0.0451
Carbon allow.	0.0479	0.0305
Rel. issue size	0.9603	0.9884

have the greatest positive average coefficient, with the largest number of bonds. In fact, a positive sign leads to increases in spread variations - and thus in the perceived riskiness of the issuer on the part of the market - whenever there are increases in the magnitude of the corresponding weather variables. Furthermore, since the regressors have been standardized before fitting the model, the size of the coefficients of different variables can be directly compared. When instead assessing the results of the tail-dependence analysis, the most relevant climate risk drivers, from a risk-management perspective, are those which have the greatest average index value, and the greatest proportion of statistically significant relationships. Upper tail dependence indices are especially relevant, whenever considering adverse effect of a variable on a country's creditworthiness, as they evaluate the joint frequency of extreme increases in spread values and in climate risk factors.

In France, as from Tables 5 and 10, the nonseasonal component of average temperatures appears as the most important risk factor, and it impacts both green and non-green bonds. This is coherent with the increase in the number of heat waves that have impacted the country (as in the report by the French Public Health Authority (2024)), as well as with its great coastal exposure to sea level rise, and to the melting of glaciers in the Alps. An evaluation of tail dependence in Table 28 shows that extreme events of all climate variables have an impact on green bonds as well as non-green ones.

As for Germany, Table 6 points to the nonseasonal component of eastward wind as the most relevant risk factor, both in terms of number of statistically significant relationships, and in terms of average coefficient size. This is consistent with the large amount of monetary damage caused in the country by winter storms (as per The Climate Change Post 2024). Interestingly, however, while one might expect damaging events linked to wind to also be connected to heavy precipitation, flood risk (as proxied by the indicator of excess soil moisture) has no damaging effect on bond spreads. This can be explained by the fact that heavy frozen precipitation (typical of winter storms) contributes little to soil moisture of the same day (Todey 2023). Concerning tail dependence, Table 30 does not highlight one particular risk factor, as all climate variables have an impact on bonds of both types. Lastly, the GARCHX analysis in Table 11 shows the role of wildfire risk in increasing the spread variance. This can be

Table 36 Issue date and size of green government bonds

ISIN	Issue size (mln €)	Total outstanding debt at bond issuance (EoY, mln €)	Issue size/ oustanding debt	Issue date	Maturity
FR0013234333	30,941.00	2,254,331.00	1.3725%	31/01/2017	25/06/2039
FR0014002JM6	16,498.00	2,823,692.00	0.5843%	23/03/2021	25/06/2044
NL0013552060	15,690.00	394,825.00	3.9739%	23/05/2019	15/01/2040
DE0001030708	8,000.00	2,340,848.90	0.3418%	09/09/2020	15/08/2030
DE0001030716	5,000.00	2,340,848.90	0.2136%	06/11/2020	10/10/2025
DE0001030724	10,000.00	2,495,538.20	0.4007%	18/05/2021	15/08/2050
DE0001030732	8,000.00	2,495,538.20	0.3206%	10/09/2021	15/08/2031
DE0001030740	5,000.00	2,561,675.40	0.1952%	07/09/2022	15/10/2027
ES0000012J07	7,236.20	1,428,133.00	0.5067%	14/09/2021	30/07/2042
IT0005438004	13,500.00	2,679,901.40	0.5037%	10/03/2021	30/04/2045
IT0005508590	6,000.00	2,757,547.40	0.2176%	13/09/2022	30/04/2035

Table 37 Number and average coefficient of statistically significant relationships with exogenous regressors, Italian government bonds ($\alpha = 0.05$)

	Green bonds			Non-green bonds		
	Avg. coeff.	Nr. (S)	Total	Avg. coeff.	Nr. (S)	Total
Italian eastw. wind (deseasonal.)	0.0247	1	2	−0.0544	22	333
Italian northw. wind (deseasonal.)	–	0	2	0.0420	37	333
Italian avg. temperature (deseasonal.)	–	0	2	−0.0684	32	333
Italian drought SMA	–	0	2	0.0885	53	333
Italian flood SMA	–	0	2	−0.0191	39	333
Italian FWI	−0.0077	1	2	−0.0247	24	333
ΔEURIBOR	–	0	2	0.0227	110	333
ΔNSS β_2	–	0	2	−0.0187	52	333
ΔNSS β_1	–	0	2	−0.0201	54	333
Log-returns of ETS carbon allowances	−0.0241	1	2	0.0266	46	333
ΔBid-ask spread	–	0	2	−0.0811	183	332
Log-returns of FTSE MIB index	–	0	2	−0.0245	105	333
ΔVIX	–	0	2	0.0178	58	333
Italian GDP %change	–	0	2	−0.0138	38	332
Italian IPI %change	−0.0299	1	2	−0.0087	62	332
Italian REER %change	0.0387	1	2	−0.2233	14	329
Italian Relative liquidity %change	−0.0131	1	2	−0.0253	33	308
Italian INFLATION RATE %change	–	0	2	−0.0221	16	306
Italian Current account balance %change	0.0363	1	2	0.0056	58	305
Italian DEBT/GDP %change	–	0	2	−0.0170	26	302
Italian FNW %change	−0.0270	2	2	−0.0279	188	288

Table 38 Number and average coefficient of statistically significant relationships with exogenous regressors, German government bonds ($\alpha = 0.05$)

	Green bonds			Non-green bonds		
	Avg. coeff.	Nr. (S)	Total	Avg. coeff.	Nr. (S)	Total
German eastw. wind (deseasonal.)	0.1635	1	5	0.0117	16	77
German northw. wind (deseasonal.)	–	0	5	0.0052	8	77
German avg. temperature (deseasonal.)	–	0	5	0.0105	6	77
German drought SMA	0.0237	1	5	0.0091	10	77
German flood SMA	−0.1098	2	5	−0.0303	2	77
German FWI	−0.0571	1	5	0.0097	8	77
ΔEURIBOR	−0.0315	2	5	−0.0481	42	77
ΔNSS β_2	0.1613	1	5	−0.0390	2	77
ΔNSS β_1	−0.0693	1	5	−0.0288	13	77
Log-returns of ETS carbon allowances	–	0	5	−0.0077	3	77
ΔBid-ask spread	−0.0901	3	5	−0.0389	31	77
Log-returns of DAX index	0.0783	2	5	0.0388	64	77
ΔVIX	0.0398	1	5	−0.0317	10	77
German GDP %change	−0.0343	1	5	−0.0116	23	77
German IPI %change	−0.0241	3	5	0.0949	11	77
German REER %change	0.0598	3	5	0.0123	26	77
German Relative liquidity %change	0.1441	2	5	0.0234	14	77
German INFLATION RATE %change	−0.0894	2	5	–	1	77
German Current account balance %change	0.0136	1	5	−0.0221	7	77
German DEBT/GDP %change	−0.1218	3	5	–	0	75
German FNW %change	–	1	4	−0.0268	20	74

Table 39 Number and average coefficient of statistically significant relationships with exogenous regressors, French government bonds ($\alpha = 0.05$)

	Green bonds			Non-green bonds		
	Avg. coeff.	Nr. (S)	Total	Avg. coeff.	Nr. (S)	Total
French eastw. wind (deseasonal.)	−0.0115	1	2	–	0	48
French northw. wind (deseasonal.)	–	0	2	–	0	48
French avg. temperature (deseasonal.)	0.0111	1	2	0.0159	13	48
French drought SMA	–	0	2	–	0	48
French flood SMA	–	0	2	−0.0167	3	48
French FWI	–	0	2	−0.0213	4	48
ΔEURIBOR	–	0	2	−0.0536	37	48
ΔNSS β_2	–	0	2	–	0	48
ΔNSS β_1	–	0	2	–	0	48
Log-returns of ETS carbon allowances	–	0	2	–	0	48
ΔBid-ask spread	−0.0924	1	2	0.0199	8	48
Log-returns of FCHI index	–	0	2	−0.0382	27	48
ΔVIX	–	0	2	−0.0305	4	48
French GDP %change	–	0	2	–	0	48
French IPI %change	–	0	2	0.0214	3	48
French REER %change	–	0	2	–	0	48
French Relative liquidity %change	–	0	2	0.0218	18	48
French INFLATION RATE %change	–	0	2	–	0	48
French Current account balance %change	–	0	2	−0.0167	7	48
French DEBT/GDP %change	−0.0239	1	2	−0.0251	28	48
French FNW %change	–	0	1	−0.0210	17	48

Table 40 Number and average coefficient of statistically significant relationships with exogenous regressors, Spanish government bonds ($\alpha = 0.05$)

	Green bonds			Non-green bonds		
	Avg. coeff.	Nr. (S)	Total	Avg. coeff.	Nr. (S)	Total
Spanish eastw. wind (deseasonal.)	–	0	1	0.0282	12	147
Spanish northw. wind (deseasonal.)	–	0	1	0.0211	12	147
Spanish avg. temperature (deseasonal.)	–	0	1	0.0123	32	147
Spanish drought SMA	–	0	1	−0.0026	24	147
Spanish flood SMA	–	0	1	0.0227	26	147
Spanish FWI	–	0	1	−0.0294	13	147
ΔEURIBOR	–	0	1	0.0122	44	147
ΔNSS β_2	–	0	1	−0.0155	19	147
ΔNSS β_1	–	0	1	−0.0301	31	147
Log-returns of ETS carbon allowances	–	0	1	0.0017	11	147
ΔBid-ask spread	–	0	1	−0.0667	65	146
Log-returns of IBEX index	–	0	1	−0.0366	88	147
ΔVIX	–	0	1	−0.0327	14	147
Spanish GDP %change	–	0	1	0.0099	22	147
Spanish IPI %change	–	0	1	−0.0151	21	147
Spanish REER %change	–	0	1	−0.0041	30	147
Spanish Relative liquidity %change	–	0	1	0.0060	16	146
Spanish INFLATION RATE %change	–	0	1	0.0055	18	146
Spanish Current account balance %change	–	0	1	0.0084	28	146
Spanish DEBT/GDP %change	–	0	1	−0.0089	16	146
Spanish FNW %change	–	0	0	−0.0186	124	144

Table 41 Number and average coefficient of statistically significant relationships with exogenous regressors, Dutch government bonds ($\alpha = 0.05$)

	Green bonds			Non-green bonds		
	Avg. coeff.	Nr. (S)	Total	Avg. coeff.	Nr. (S)	Total
Dutch eastw. wind (deseasonal.)	–	0	1	0.0173	4	24
Dutch northw. wind (deseasonal.)	–	0	1	0.0095	1	24
Dutch avg. temperature (deseasonal.)	–	0	1	−0.0079	2	24
Dutch drought SMA	0.0887	1	1	–	0	24
Dutch flood SMA	–	0	1	–	0	24
Dutch FWI	–	0	1	0.0323	3	24
ΔEURIBOR	−0.0345	1	1	−0.0477	13	24
ΔNSS β_2	–	0	1	0.0123	2	24
ΔNSS β_1	0.0213	1	1	−0.0094	1	24
Log-returns of ETS carbon allowances	–	0	1	−0.0247	4	24
ΔBid-ask spread	–	0	1	−0.0515	7	24
Log-returns of AEX index	–	0	1	0.0313	3	24
ΔVIX	–	0	1	−0.0233	5	24
Dutch GDP %change	–	0	1	−0.0586	1	24
Dutch IPI %change	–	0	1	−0.0203	17	24
Dutch REER %change	–	0	1	0.0294	5	24
Dutch Relative liquidity %change	0.0932	1	1	0.0140	6	24
Dutch INFLATION RATE %change	–	0	1	−0.0390	1	24
Dutch Current account balance %change	–	0	1	–	0	24
Dutch DEBT/GDP %change	–	0	1	–	0	24
Dutch FNW %change	–	0	1	−0.0276	14	24

connected to recent events, as the fires in Meppen and Lübtheen of 2018 and 2019, have highlighted this climate factor as a threat growing in importance.

In Italy, as from Tables 7 and 12, drought risk emerges as the most impactful climate risk factor for non-green debt, due to it having the largest positive coefficient, as well as the greatest number of statistically significant relationships with outstanding bonds. This result is understandable, as the gradual desertification of portions of Italy is one of the fastest-emerging manifestations of climate change in the country. Its effect is only observed on non-green bonds, however, showing a different treatment, on the part of the market, of green instruments with regards to this risk. Interestigly, as can be seen in Table 37 the log-returns of ETS carbon allowances have the second-largest number of statistically significant relationships with bond spreads, among the climate-relevant regressors. They impact non-green bonds adversely (with a positive average coefficient) and green bonds favorably (with a negative coefficient). This indicates that the market gives a price to transition risk in Italian government bonds, but it requires a positive premium from traditional bonds, and instead lowers its demand for compensation, in the case of green bonds. This result is supported by the ARIMAX-GARCHX model fit, which highlights that carbon allowances increase the volatility of traditional debt instruments, but not of green bonds. As for tail dependence, in Table 31, extreme events have an impact on green bonds as well as non-green ones, for most variables, but less frequently on the former than the latter. Carbon allowances again emerge as of interest, as green bonds are only affected in the lower tail (resulting in a decrease in the spread), while traditional bonds are affected in both the upper and the lower tail.

As for the Netherlands, Table 8 highlights the nonseasonal component of eastward wind and the fire weather risk index as the most significant risk factors for traditional bonds, although the number of significant relationships is limited. While the first variable is of understandable importance, in a country known for its windiness, it is perhaps less expected for the market to be pricing wildfire risk in northern Europe. However, the significance of this factor also emerges from the GARCHX models in Table 13, together with droughts. Looking at historical data provides insight into why this concern has become of increasing timeliness, over the last decade. As per Stoof et al. (2024), just from 2017 to 2022, 611 wildfires occurred in the Netherlands, burning an average of 405 hectares per year. The main source of danger is the relatively new nature of this type of risk. Because of its novelty, it is often "unaccounted for [...] due to low awareness and preparedness amongst major stakeholders and the general public" and harder to tackle, upon occurrence, than in the Mediterranean area, as Dutch fire services "tend to be specialized in urban fires rather than landscape fires", Stoof et al. (2024). Interestingly, the one green bond included in the sample only exhibits one significant relationship, and it is with the drought risk index. Once again, the pricing of this risk on the part of the market is backed by historical weather events: this bond, with an age of less than four years - substantially lower than that of the average traditional bonds in the sample - reflects an exposure to the sudden appearance of yearly heatwaves and droughts on the Dutch territory, which have begun in 2018 (as per Utrecht University press release 2022). These extreme events are particularly damaging to Dutch agriculture. One final element of note is the Dutch exposure to EU carbon allowances (the transition risk proxy): as can be seen in Table 41, the market is rewarding traditional Dutch government bonds (with a decrease in their average spread), when the overall level of transition risk increases. Additionally, the green bond is not impacted by this factor.

Finally, the most relevant climate risk variables in Spain are the nonseasonal component of average temperature, drought risk, and flood risk. These results hold both for the mean of the process, as per Table 9, as well as for the variance of the bond spreads, as per Table 14. The first two risk factors are coherent with the number of heat waves which affect the territory every year (Serrano-Notivoli et al. 2022), with the "persistent alert drought conditions" of the country (EU Science Hub 2024), with the great coastal exposure of Spain to sea level rise, and with the importance of the country's agricultural sector for its GDP. As for flood risk, which might be less expected, it is actually the main source of climate-related damage for the country, as it represents the 70% of the total indemnities paid out from 1987 to 2023 by the "Extraordinary Risk Insurance" Scheme in Spain, a compulsory government catastrophic risk insurance programme (as per the report by the Consorcio de Compensación de Seguros (2024)). In terms of tail dependence, Table 29 shows that extreme events of all climate variables have an impact non-green bonds, while the green bond in the sample only reacts to extreme temperatures, wildfires, and wind levels.

While differences in the most relevant risk drivers of each country find confirmation in the physical features of each territory, and therefore in their direct exposure to the corresponding climate events, some further information could be captured by the market. Embedded in spread movements are investor beliefs about the creditworthiness of the underlying entity, implying that the climate resilience of a country - not just its exposure - could also be priced. The impact of some risk factors on spreads might be dampened by credible adaptation policies, able to influence investor beliefs. Cross-border differences might then emerge, with some countries being proportionally less affected than others, due to their greater or more effective investment in climate-risk mitigation and adaptation. Testing these theories is a promising area of future study. We therefore report some information on the National Adaptation Plans and National Adaptation Strategies of the countries under study, to hopefully provide some useful context.

France and Germany are the early adopters, in this group of countries, of governmental climate risk awareness and mitigation strategies. In 2006, the French government validated the *Stratégie nationale d'adaptation au changement climatique* and in 2011 it developed its first, of three, National Plans for Climate Change Adaptation (PNACC). Germany closely followed, adopting the German Strategy for Adaptation to Climate Change in 2008. After a number of adaptation plans, in 2023 Germany became the first EU country to sign a legally binding climate adaptation law, the Federal Climate Adaptation Act, requiring federal, state, and municipal authorities to develop adaptation strategies and objectives. Spain and Italy had slower starts: Spain developed its first national adaptation plan in 2006, but only adopted a National Plan for Adaptation to Climate Change in 2020, while Italy developed its first National Adaptation Strategy in 2015, and approved the National Plan for Adaptation to Climate Change in late 2023. Finally, the Netherlands established their National Adaptation Strategy only in 2016, but the country has been active on the front of water risk mitigation since 2009, with its Delta Programme.

Quantifying country-level investment in climate adaptation efforts is not an easy task. We therefore only list some of the more substantial measures that have been adopted to date. France has established the Major Natural Risk Prevention Fund (FPRNM) of undisclosed size, while Italy has allocated 39% of its €194.4 billion National Recovery and Resilience Plan (NRRP), approved in 2021, to climate objectives. Spain has an "Extraordinary Risk Insurance" Scheme in place and approved a €2.2 billion drought response plan in 2023. Finally, according to its 2025 outlines programme, the Dutch Delta Programme is expected to cost €28 billion between 2015 and 2050.

6.1 Framework uses and policy implications

The modeling approach proposed in this paper aims to provide a methodology for the investigation of the link between climate risk and the spreads of sovereign bonds. By evaluating market reactions, it is possible to identify which factors most impact bond spreads, and therefore to evaluate current market attitudes towards climate risk. This can inform mitigation and adaptation strategies based on the most financially material climate threats, given the knowledge of which risk factors are currently priced by the market. Green investment on the part of countries could therefore be targeted with precision towards the identified factors. Additionally, this procedure enables the identification of climate risk proxies to which the market is not reactive, for each country. A comparison with non-financial evaluations of existing threats can highlight potential blind-spots for the market, indicating climate risk which is currently underestimated. The framework presented in this work could also play a role in completing the understanding of climate risk across borders. This could assist in designing data-driven policy, which would lead towards climate finance strategies that reflect the risk heterogeneity that is present across EU countries.

From a practical standpoint, one of the main advantages of this framework is that it provides a transparent (econometric) link between climate variables and financial market outcomes. From the risk management perspective, climate risk hedging strategies could be improved by the ability to quantify how specific climate factors impact risk in a particular country. The models proposed in this work are well-suited for in-sample analysis, but limitations in their forecasting power are present, though they mostly surpass the benchmark model performance. Forecasting power might benefit from the inclusion of more information, as it is worth noting that a large proportion of the exogenous regressors has a low frequency of observation, due to its macroeconomic nature. Attempts could be made to obtain data (or proxies of it) at a higher frequency. Overall, the predictive power of such time series models decreases when the forecast window is extended, making the evaluations more reliable in the short term - if used, for example, in the calculation of spread variance for Value-at-Risk assessments, stress testing, or risk management tasks. A rolling-window calibration procedure, however, leads to results that are stable in terms of accuracy also for the longer term, making the model suitable, for example, for scenario analysis. The ARIMAX-GARCHX models could be particularly useful for climate Value-at-Risk assessments, as they provide a forecast mechanism for future spread variance. In the context of scenario analysis, long-term trends could be projected in light of forecasts of climate risk factors in different settings. An illustration is provided in the next paragraph, where the ARIMAX-GARCHX model is integrated in the 2024 Fit-for-55 Scenario Analysis Exercise by the European Systemic Risk Board, European Central Bank, and the European Supervisory Authorities.

6.2 Scenario Analysis

The cross-validation analysis carried out in Section 5.1.3 highlights the usefulness of climate regressors for improving forecast accuracy for a number of government bonds. What emerges is also that the predictive accuracy of the model, though imperfect, remains stable as the forecast window length increases, suggesting that the ARIMAX framework can be applied to longer-term projections, where a lower degree of accuracy may be acceptable. We therefore illustrate how the framework could be used for the purpose of the scenario analysis based on the most recent example carried out in the European Union: the 2024 Fit-for-55 Scenario Analysis Exercise.

An important disclaimer is made in the Exercise report by the European Supervisory Authorities (2024), which also applies to the analysis in this paper: "*As with all forward-looking projections, the outcomes are subject to inherent uncertainty, and to the associated modelling/estimation error linked to the novelty of the climate stress testing approaches as well as data quality concerns.*[...]*Hence the outcomes of the exercise need to be carefully considered within the bounds of the designed scenarios*".

The assumption underlying all the scenarios in the exercise is the adoption by the EU of the policies set out in the "Fit for 55" package, which aims to reduce greenhouse gas emissions by 55% by 2030. There are three settings: a baseline, which assumes successful policy implementation without major shocks, a first adverse scenario, with a rapid divestment from carbon-intensive assets ("run-on-brown"), and a second adverse scenario, that combines transition risks with other macroeconomic stress factors, such as geopolitical risk. Shocks are heterogeneous across countries and affect financial assets differently. Government bonds play an important role in the evaluation of market risk: they represent 74% of the market portfolio at fair value of banks, 24% of total investments by insurance companies, and 25% of total investments by Institutions for Occupational Retirement Provision. The latter two types of institutions hold many fixed income assets, with durations that match their liabilities, to receive predictable cash flows coinciding with obligations and to help manage interest rate risk.

In the exercise, market risk losses are generated by applying a one-off financial shock ($\Delta P_{b,i,t+252}$) to the fair value of the instrument ($P_{b,t}$) at a starting time t, which is set as the last observation of 2022. The shock represents the scenario realization at the end of the subsequent year, a time which we denote as $t + 252$, referring to the number of business days in one year. In the case of government bonds, the shock to the yield of a bond b in scenario i after one year ($\Delta y_{b,i,t+252}$) is defined as[1]

$$\Delta y_{b,i,t+252} = \frac{\Delta r_{i,t+252} + \Delta s_{b,i,t+252}}{10000},$$

[1] This formulation is taken from the cross-sectoral analysis, Appendix II p. 77 of European Supervisory Authorities (2024).

Table 42 Shocks to government bond spreads. Absolute changes (basis points), from European Systemic Risk Board (2023)

Country	Scenario	1Y	2Y	5Y	10Y	20Y	30Y
Germany	Baseline	3	5	7	7	11	16
	Adverse 1	15	17	19	23	27	31
	Adverse 2	97	85	74	68	57	56
France	Baseline	3	5	7	7	11	16
	Adverse 1	15	17	19	23	27	31
	Adverse 2	97	85	74	68	57	56
Italy	Baseline	16	17	19	24	29	29
	Adverse 1	30	32	34	40	41	51
	Adverse 2	290	279	267	254	236	246
Netherlands	Baseline	3	5	7	7	11	16
	Adverse 1	15	17	19	23	27	31
	Adverse 2	97	85	74	68	57	56
Spain	Baseline	16	17	19	24	29	29
	Adverse 1	30	32	34	40	41	51
	Adverse 2	290	279	267	254	236	246

where $\Delta r_{i,t+252}$ and $\Delta s_{b,i,t+1}$ are the shocks to the risk-free rate and to the bond spread in scenario i after 1 year, in basis points. The shock to the bond price ($\Delta P_{b,i,t+1}$ is then approximated as

$$\Delta P_{b,i,t+1} = P_{b,t}\Big(- \Delta y_{b,i} \cdot D_b + \frac{1}{2}\Delta y_{b,i}^2 \cdot C_b\Big),$$

where D_b and C_b are the modified duration and convexity of bond b, and $P_{b,t}$ is the bond fair value at the starting point. Then, the revalued government bond price under scenario i is

$$P_{b,i,t+252} = P_{b,t} + \Delta P_{b,i,t+252}.$$

In the Fit-for-55 Scenario Analysis Exercise, the shocks to government bond spreads under each scenario ($\Delta s_{b,i}$) are provided by the European Systemic Risk Board, by country and for a number of maturities. The values of the shocks for the countries analysed in this work are provided in Table 42[2].

The model introduced in this paper can enrich the framework by allowing for the computation of each shock to the government bond spread ($\Delta s_{b,i}$) as a function of the impact of the different risk factors, including physical climate risk, through the ARIMAX representation. This offers a direct econometric link that can be tailored to each instrument. For illustrative purposes, we perform these computations under the three scenarios of the original exercise, but they can be extended to further scenarios

[2] Excerpt of Table A7 of European Systemic Risk Board (2023).

and projections. The shocks to macroeconomic variables under each setting, whenever available, are the ones provided by European Systemic Risk Board (2023), and are otherwise set to their historical average value. The shocks to the physical risk drivers are extracted from their projected pathways in the NGFS Nationally Determined Contributions (NDC) scenario (or the one equivalent to it, if a different framework is used by the data providers), which underlies all three settings[3]. Further details about the data sources and the procedure are provided in Appendix D.

In order to enhance the meaningfulness of the illustration, we restrict the scenario analysis to the (C) bonds identified in Section 5.1.3, for which the ARIMAX model with climate regressors provides an improvement in forecast accuracy. Table 43 holds the results of the scenario analysis. Mirroring Table 42, the year-end shocks in the bond spreads are provided, in basis points, by country, scenario, and bond maturity. For some countries, some maturities are blank, as there were no (C) bonds to cover them. We find that the size of the shocks is generally higher than in Table 42, as the scenario analysis that we perform also explicitly includes physical risk projections. The only exception is represented by the Netherlands, for which the physical risk exposure had already been found to be very limited, in the mean of the ARIMAX process (Table 8). Additionally, and unsurprisingly, the shocks are greatest for all countries in Adverse Scenario 2, with results more pronounced for Spain and Italy, similarly to Table 42. Finally we remark that, according to our estimates, Adverse Scenario 2 leads to shocks for Germany that are nearer to the Italian values than to the French. This is in line with the middle-of-the road position of the country, in terms of climate risk exposure, that was highlighted throughout the present work.

We conclude the section by repeating the limitations of this exercise which, as any type of scenario analysis, is limited to the availability and quality of the projected future paths of the exogenous variables influencing the quantity under study. For this reason, this section should be understood as providing an illustration of a methodology, rather than providing definitive values.

7 Conclusions

The aim of this work was to compare the response to climate risk of green and non-green bonds issued by the same Eurozone governments, and to identify the main drivers of climate risk by country. We selected sovereign entities on the basis of green bond issuance. We evaluated the impact on bond spreads of a number of potential physical and transition risk drivers, identified in line with the ECB climate stress tests and the extant literature, through the fitting of ARIMAX models and the use of tail dependence measures.

The results highlighted interesting differences between the sovereign issuers, which could be divided into two groups: France, the Netherlands, and Germany, on the one hand, and Italy and Spain, on the other. In the first group, there was little to no observable difference between the sensitivity to climate risk of the green and non-

[3] The shocks of the Fit-for-55 Scenario Analysis Exercise are calibrated by combining the 2023 EU-wide stress test scenarios (2023-2025) with the NGFS NDC scenario (2023-2030) published in Phase IV (November 2023).

Table 43 Shocks to government bond spreads. Absolute changes (basis points), from scenario analysis

Country	Scenario	5Y	10Y	20Y	30Y
France	Baseline	10	32	14	–
	Adverse 1	15	32	15	–
	Adverse 2	38	77	59	–
Germany	Baseline	26	23	–	–
	Adverse 1	27	25	–	–
	Adverse 2	226	149	–	–
Italy	Baseline	192	156	143	181
	Adverse 1	193	156	145	181
	Adverse 2	236	184	264	244
Netherlands	Baseline	–	–	2	–
	Adverse 1	–	–	3	–
	Adverse 2	–	–	26	–
Spain	Baseline	276	214	39	126
	Adverse 1	278	228	58	136
	Adverse 2	289	363	349	145

green bonds. In the second group, however, green bonds displayed a lower number and smaller size of significant relationships with the climate risk proxies, compared to the non-green ones.

We put forth two potential explanations for the difference between the two groups. The first is the greater average age of the French and Dutch green government bonds, as the longer time series of their observations could include a proportionally higher number of extreme weather events, thus increasing the occurrence of simultaneous movements and leading to higher levels of tail dependence. The second explanation is the relative scarcity of green bonds compared to the country's total outstanding debt. Notably, Dutch and French green government debt is proportionally the most abundant, among all sample countries. If market appetite for sustainable treasury investment of those countries is comparatively more satisfied, given the lower level of relative scarcity, it could explain a market treatment that is more similar to that of traditional bonds. Conversely, Spanish and Italian green bonds are, proportionally, up to eight times less abundant and constitute less than 1% of the respective countries' total outstanding debt. Then, their lower reactivity to climate risk could be driven by their scarcity. A further analysis based on k-means clustering provides empirical support to this hypothesis.

Overall, what emerges is an unsatisfied investor appetite for Eurozone green bonds, therefore hinting at more space for growth in their issuance, in particular in the Spanish and Italian cases. This, however, also indicates a degree of under-development of the green debt market, which could be affecting the results of this analysis. Still, the convergence between the behavior of green and non-green debt in the more mature French and Dutch markets suggests that the climate risk exposure of non-green debt can provide reliable insights for the purpose of financial stability.

The implications for financial stability are also discussed, highlighting the most important climate risk factors for every country. The results can be connected to current events and to past disasters, providing further insight into the current pricing, by markets, of each type of risk. Lastly, policy implications and practical uses of the methodology are discussed, and an illustration of a potential application for scenario analysis is presented.

There are, however, some limitations to our work. In particular, the heterogeneity of bonds, even by the same issuer, had a great impact in our ability to generalize results. We controlled for liquidity, among the exogenous regressors of the ARIMAX models, in order to account for one of the possible determinants of the divergence in the behavior of some time series, but other explanations or approaches could lead to superior results. Furthermore, many of the exogenous regressors of the ARIMAX models for government bonds had a low frequency, due to their macroeconomic nature. This biased their significance downward. Potential future extensions could attempt to model them directly, perhaps by linking them to variables available at shorter time intervals, in order to obtain estimates at a higher frequency. Finally, the substantially lower number of green bonds than of non-green ones limits on the comparability of average measures across green and non-green bonds of the same issuer, as proportions take on less nuanced values when the numerator is very small, biasing them towards the extremes. For this reasons, we believe that the conclusions drawn in this study cannot be generalized beyond their current state. Future work, if aiming to further pursue the comparison of green and traditional bonds by the same issuer, could potentially focus on a much smaller traditional bond sample, with features as similar as possible to the few available green bonds.

These findings hopefully contribute valuable insights into the evolving landscape of sustainable finance, for the development of credit-risk models and investment strategies that account for climate risk, and for macro-economic considerations on the topic of financial stability. Further analyses could be aimed at refining the model, at extending the sample of countries, at investigating empirical links between the climate risk exposure of each country to that of firms located on its territory, and at exploring potential strategies to increase the resilience of the financial system to environmental vulnerabilities. This could help regulators refine climate stress testing and assessment models for financial entities, as well as understand the potential risk-mitigating role of green investment for tackling climate-related challenges.

Appendix A Selection of the model for bond spreads

In this Appendix we report more details on the procedure that led to the selected model for bond spreads. A first attempt involved the fit of a preliminary linear regression to the stationary spread increments $\Delta s_{b,t} = (1 - L)s_{b,t} = s_{b,t} - s_{b,t-1}$, with Heteroskedasticity- and autocorrelation-consistent (HAC) estimators of the variance-covariance matrix. The choice of the HAC estimator is motivated by an observation of the Partial Auto-Correlation Functions of the spread increments, which highlight the presence of autocorrelation for many of them, and by Engle's Lagrange Multiplier test, which finds heteroskedasticity in their time series. The preliminary regression has the following form

$$\Delta s_{b,t} = \beta_{b,0} + \sum_{j=1}^{n} \beta_{b,j} X_{b,j,t-1} + \epsilon_{b,t},$$

for each bond b. These preliminary regressions are instrumental for two purposes. The first is the selection of the relevant exogenous regressors $X_{b,j,t-1}$, whenever multiple proxies for the same variable of interest are available, and the second is the study of the time series of the residuals $\epsilon_{b,t}$, in order to evaluate their features and to further refine the structure of the final model.

A.1 Selection of the relevant exogenous regressors

Concerning the first goal, multiple potential proxies are available for the following variables of interest: drought risk, transition risk, slope and convexity of the EURIBOR yield curves. In order to avoid multicollinearity issues, for each variable of interest only one proxy can be included in the final model. In order to select it, for all these variables, the models with each "candidate" risk proxy are fit separately and then compared. The proxy with the greater number of statistically significant relationships with the time series of the spreads is then selected for inclusion in the final model. The statistical significance of each relationship is evaluated via the p-value of the t-test of the corresponding coefficient, at the 95% confidence level. The regressions are run multiple times, for all combinations of the potential proxies. Table 44 holds the number of statistically significant relationships of each proxy, with results taken from a final model run in which all other variables of interest are represented by their optimal proxy.

Table 44 Number of statistically significant relationships of each proxy at the 5% significance level (preliminary model)

Variable of interest	Proxy 1	Proxy 2
Drought risk	Combined Drought Indicator	Soil Moisture Index Anomaly
	18	41
Transition risk	Integrated volatility of futures on EU carbon allowances	EU carbon allowance log-returns
	79	102
Yield curve slope	Difference between rates	β_1 NSS coefficient
	105	176
Yield curve convexity	Squared spot rate	β_2 NSS coefficient
	68	99

When seeking for a drought risk proxy, the Combined Drought Indicator and the Soil Moisture Index Anomaly (SMA) are considered and, after evaluation, SMA emerges as the more statistically significant of the two and is thus exclusively chosen. As for transition risk, the log-returns of EU carbon allowances and the integrated volatility of futures contracts on carbon allowances are considered. The former are found to have the stronger explanatory power and are therefore uniquely selected. Concerning the tenor of EURIBOR rates, multiple alternatives are considered: a fixed one for all bonds, or a different one for each individual bond, matched either to its maturity or to its duration. All alternatives are fit, one at a time, and the last one is chosen, as it displays the highest explanatory power. For every day in the sample window, the duration of each bond is therefore computed and the EURIBOR rate with the corresponding duration is interpolated from the yield curve of that date, and its one-period increment is used as a regressor. For the slope of the yield curve, one proxy can be the difference between the benchmark yield of a long maturity (often 10 years) and one with a shorter one. A different potential proxy is the β_1 coefficient of the NSS interpolation scheme. For the convexity, the two options are the square of the benchmark yield (matched to the maturity or to the duration of each bond), and the β_2 coefficient of the NSS interpolation scheme. The NSS parameters β_1 and β_2 resulting from fitting the model to the daily benchmark yields is selected in the final version of the model, as they are found to have the greatest explanatory power.

A.2 Refining the final model

These results are however only of a preliminary nature, as an analysis of the residuals reveals that the model is not yet well-specified. Inference on the HAC-based coefficients might be biased for the bonds having shorter windows of observations, such as the green ones. Additionally, the time-varying nature of the variance could be of interest for inference and forecasting purposes, especially if it is influenced by exogenous variables. The OLS-HAC model, however, only provides a constant estimate of residual variances. For these reasons, we proceed by selecting a model which is explicitly able - to the best of our ability - to account for the specific features of the data. Since the objective of this study is to provide reliable inference on the coefficients of the regressors, most especially of the climate risk factors, special attention is paid to this part of the work.

The Jarque-Bera test shows that it is not possible to rely on the underlying normality assumption, as the residuals reject the null hypothesis of normality for almost all bonds in the sample. Table 45 shows the proportion of bonds rejecting the Jarque-Bera test at the 99% confidence level, by country, and the average kurtosis of the residuals in the sample. We therefore select a Student-t distribution for the residuals, which is also able to account for the few Gaussian cases in the sample, by letting the degrees of freedom increase.

Additionally, since the Breusch-Godfrey test shows the presence of autocorrelation, we proceed to investigate if Moving-Average effects are also present. We first alter the model by incorporating p Auto-Regressive (AR) lags of the dependent variable, i.e. $(\sum_{i=1}^{p} \varphi_{b,i} L^i)(1-L)s_{b,t} = (\sum_{i=1}^{p} \varphi_{b,i} L^i)\Delta s_{b,t} = \varphi_{b,1}\Delta s_{b,t-1} + \varphi_{b,2}\Delta s_{b,t-2} + \ldots +$

Table 45 Diagnostics on the residuals of preliminary models

	Proportion of bonds rejecting the Jarque-Bera test	Average residual kurtosis
Germany	100.0%	23.41
Spain	99.32%	112.31
France	100.0%	35.12
Italy	95.82%	20.8
Netherlands	100.0%	44.89

Table 46 Proportion of bonds rejecting the null hypothesis of homoskedasticity of Engle's test

	Proportion of bonds rejecting Engle's test
Germany	97.56%
Spain	87.84%
France	100.0%
Italy	85.07%
Netherlands	100.0%

$\varphi_{b,p}\Delta s_{b,t-p}$. The value of p is selected as the one minimizing the Bayes Information Criterion. Then, after observing the behavior of the Partial Autocorrelation Functions (PACF) and of the Autocorrelation functions (ACF) of the corresponding residuals, we see that Moving-Average (MA) effects might be present in some time series. For this reason, the overall model is chosen to be of the ARIMAX type. The number of AR and MA lags is optimized simultaneously, by fitting multiple combinations for each bond and then selecting the one with the lowest Bayes Information Criterion. Each can be equal to zero, whenever the time series requires it. Whenever both are, the underlying model becomes a standard linear regression, save for the distribution of the increments. Finally, we explicitly account for the presence of heteroskedasticity, detected via Engle's test, by modeling the variance with a classical GARCH model. The proportion of bonds rejecting the null hypothesis of homoskedasticity of Engle's test is reported in Table 46. Once again, the algorithm is free to choose GARCH orders equal to zero whenever the time series requires it. An attempt is also made to fit a GARCHX model on the residual variances, to assess whether they are impacted by exogenous regressors.

Appendix B Extraction of standardized residuals

B.1 Non-seasonal component of average daily temperature

In line with Benth and Saltyte-Benth (2012), the continuous-time model selected for the non-seasonal component of temperature is of the CARMA(p,q) type. The lag order is selected by observing the partial autocorrelation function of the data, which

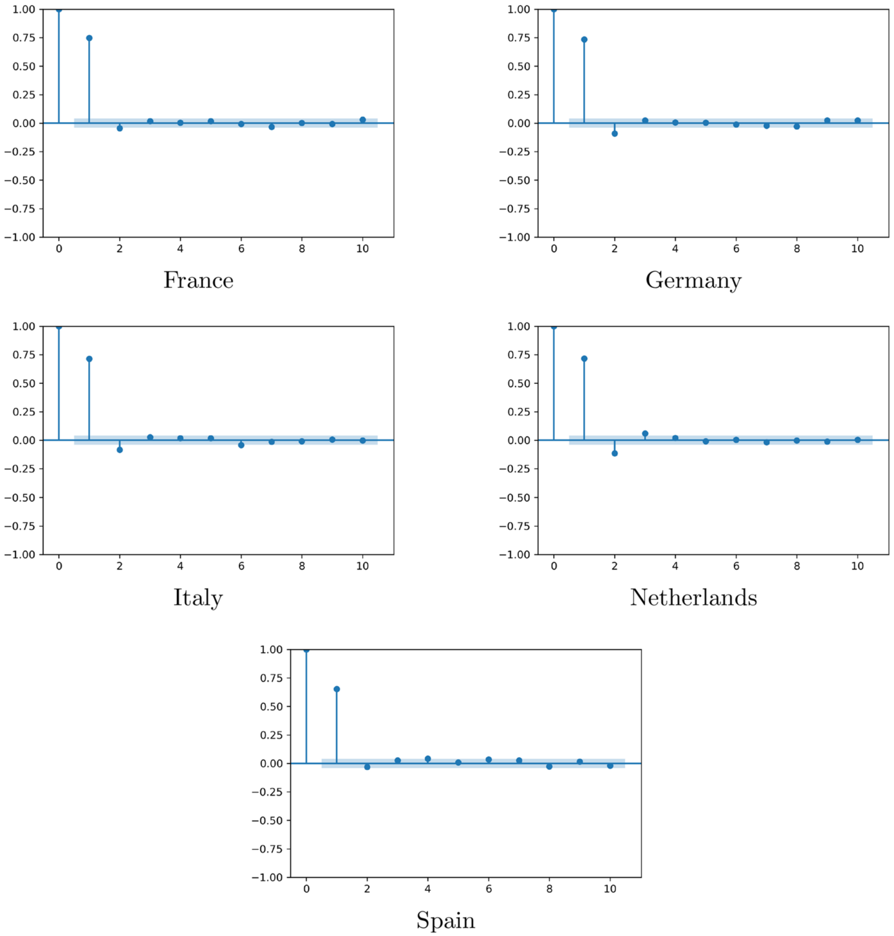


Fig. 8 Partial Autocorrelation Functions for the non-seasonal component of average daily temperature

Table 47 Skewness, kurtosis, and p-value of Jarque-Bera test on AR(2) model residuals

	Skewness	Kurtosis	P-value
France	−0.251	5.177	0.0
Germany	−0.134	4.949	0.0
Italy	−0.294	4.637	0.0
Netherlands	−0.005	4.129	0.0
Spain	−0.177	4.203	0.0

is reported in Figure 8. For all countries involved, the model with $p = 2$ and $q = 0$ is sufficient.

The next issue is the selection of the distribution of the Lévy process inside the CARMA model. In Benth and Saltyte-Benth (2012), a Brownian Motion is selected. Therefore, AR(2) models with Gaussian increments are fit to the data, but the Jarque-

Table 48 CARMA(2,0) parameters of non-seasonal average temperature

	a_1	a_2
France	1.216	0.249
Germany	1.166	0.245
Italy	1.210	0.293
Netherlands	1.172	0.290
Spain	1.311	0.343

Bera test on the residuals rejects, for all countries, the null hypothesis of skewness and kurtosis matching a normal distribution, as can be seen in Table 47. Hence, in contrast with their approach, we do not opt for Gaussian noise, but for Normal-Inverse-Gaussian increments. This distribution is selected in light of its ability to accommodate varying levels of skewness and kurtosis, which are observed in the data, and also because of its past use as a driver of CARMA processes in the financial literature, as in Benth and Saltyte-Benth (2004).

The discretization scheme follows Lavagnini (2020), who proves that, for a uniform time step Δt

$$
\begin{aligned}
&\frac{1}{(\Delta t)^{p-1}}\sum_{j=0}^{p}(-1)^j z_j^p \gamma_{i,t+(p-j)\Delta t} = \\
&-\sum_{i=1}^{p} a_{p-i+1}\frac{1}{(\Delta t)^{i-2}}\sum_{j=0}^{i-1}(-1)^j z_j^{i-1}\gamma_{i,t+(i-1-j)\Delta t} + \Delta L_{t+(p-1)\Delta t},
\end{aligned}
$$

where the coefficients z_j^i are defined as $z_0^i = z_i^i = 1$ for $i = 1, \ldots, p$, and, through the recursion

$$
z_j^i = z_{j-1}^{i-1} + z_j^{i-1}, \quad \text{for } j = 1, \ldots, p-1 \text{ and } i \geq 2.
$$

Then, taking $p = 2$, we have

$$
\begin{aligned}
&z_0^2\gamma_{i,t+2\Delta t} - z_1^2\gamma_{i,t+\Delta t} + z_2^2\gamma_{i,t} = \\
&\quad - a_2(\Delta t)^2\gamma_{i,t+} - a_1 z_0 \Delta t \gamma_{i,t+\Delta t} + a_1 z_1 \Delta t \gamma_{i,t} + \Delta t \Delta L_{t+\Delta t},
\end{aligned}
$$

where $z_0 = z_0^2 = z_1 = z_2^2 = 1$ and $z_1^2 = 2$, yielding

$$
\begin{aligned}
\gamma_{i,t+2\Delta t} &= (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} + \Delta t(L_{i,t+2\Delta t} \\
&\quad - L_{i,t+\Delta t}) \\
&= (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} + \Delta t \Delta L_{i,t+\Delta t} \\
&= (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} + \Delta t(\Delta L_{i,t+\Delta t} \\
&\quad \pm \mathbb{E}[\Delta L_{i,t+\Delta t}])
\end{aligned}
$$

Table 49 Estimated parameters of the NIG distribution of $\xi_{i,t+\Delta t}$

	α	β	δ	μ_ξ
France	0.395	−0.016	2.443	0.101
Germany	0.310	−0.026	2.252	0.188
Italy	0.404	−0.042	2.326	0.245
Netherlands	0.370	0.012	2.740	−0.087
Spain	0.461	−0.036	2.172	0.168

$$
\begin{aligned}
&= \mathbb{E}[\Delta L_{i,t+\Delta t}] + (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} \\
&\quad + \Delta t(\Delta L_{i,t+\Delta t} - \mathbb{E}[\Delta L_{i,t+\Delta t}]) \\
&= \Delta t\mathbb{E}[\Delta L_{i,t+\Delta t}] + (2 - a_1\Delta t)\gamma_{i,t+\Delta t} + (-1 + a_1\Delta t - a_2(\Delta t)^2)\gamma_{i,t} \\
&\quad + \Delta t\xi_{i,t+\Delta t}.
\end{aligned} \tag{B1}
$$

Here, $\Delta L_{i,t+\Delta t} = L_{i,t+2\Delta t} - L_{i,t+\Delta t}$ and $\Delta L_{i,t+\Delta t} \sim NIG(\alpha, \beta, \delta, \mu)$, with $t \in \mathbb{N}_0$. Then, $\mathbb{E}[\Delta L_{i,t+\Delta t}] = \mu + \frac{\delta\beta}{\zeta}$ and $Var(\Delta L_{i,t+\Delta t}) = \frac{\delta\alpha^2}{\zeta^3}$, where $\zeta = \sqrt{\alpha^2 - \beta^2}$. Furthermore, $\xi_{i,t+\Delta t} = \Delta L_{i,t+\Delta t} - \mathbb{E}[\Delta L_{i,t+\Delta t}]$, meaning that $\xi_{i,t+\Delta t} \sim NIG(\alpha, \beta, \delta, \mu_\xi = \frac{-\delta\beta}{\sqrt{\alpha^2-\beta^2}})$, $\mathbb{E}[\xi_{i,t+\Delta t}] = \mathbb{E}[\Delta L_{i,t+\Delta t} - \mathbb{E}[\Delta L_{i,t+\Delta t}]] = 0$, and $Var(\xi_{i,t+\Delta t}) = Var(\Delta L_{i,t+\Delta t} - \mathbb{E}[\Delta L_{i,t+\Delta t}]) = Var(\Delta L_{i,t+\Delta t}) = \frac{\delta\alpha^2}{\zeta^3}$.

Maximum likelihood is used to estimate the parameters of the linear regression in Eq. (B1), taking $\Delta t = 1$ day. The estimates of the NIG distribution parameters are reported in Table 49, while the CARMA(2,0) parameters are recovered by exploiting their relationship with coefficients of the first and second autoregressive terms, as the former equals $(2 - a_1\Delta t)$ and the latter $(-1 + a_1\Delta t - a_2(\Delta t)^2)$. The corresponding estimates are in Table 48.

B.2 ETS Carbon allowances

The discretized carbon returns in Eq. (8), conditional on the knowledge of the value of $N_{t+\Delta t} - N_t = n$, follow a normal distribution. More precisely, since $\sigma_i\sqrt{\Delta t}Z \sim N(0, \Delta t\sigma_i^2)$ and $y_j \sim N(m, \delta^2)$, $\forall j$, the conditional distribution of $\gamma_{i,t+\Delta t}$ is

$$
\gamma_{i,t+\Delta t} \sim N\Big(\left(\mu_i - \lambda_i k_i - \frac{\sigma_i^2}{2}\right)\Delta t + n\cdot m, \quad \sigma_i^2\Delta t + n\cdot\delta^2\Big)
$$

Table 50 Estimated parameters of the carbon allowance returns

μ_i	σ_i	λ_i	m	δ	k_i
0.001578	0.018126	0.396059	−0.002818	0.034836	−0.002209

and we denote the corresponding density by $f_n(x)$. Then, their unconditional density is

$$f(x) = \sum_{n=0}^{+\infty} e^{-\lambda_i \Delta t} \frac{(\lambda_i \Delta t)^n}{n!} f_n(x).$$

The parameters can then be calibrated via maximum likelihood. The series in the unconditional density is truncated at 50 jumps per unit of time $\Delta t = 1$ day in Table 50.

Appendix C Model forecast performance details

This appendix holds the goodness of fit measures of the bonds for which the ARIMAX-GARCHX model *with* climate risk factors leads to a better forecast accuracy than the models *without* climate risk factors. These bonds are denoted as (C) bonds in Section 5.1.3. Table 51 presents the measures of these bonds for both models and for the different forecast horizons, showing that the error values are overall lower for the ARIMAX-GARCHX models *with* climate risk factors. The appendix also holds Tables 67, 76 with the average coefficient, standard deviation, and number of statistically significant relationships of green and non-green bonds, across rolling windows and for different forecast horizons. The standard deviations are overall rather low, highlighting stability in the value of the fitted coefficients. Additionally, the variations across different forecast horizons are limited. This supports the robustness of the model for identifying structural relationships in Tables 52, 53,54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73,74, 75.

Table 51 NRMSE of (C) bonds for ARIMAX-GARCHX models with and without climate risk factors

	2	6	10	45	100
Italian (C) green bonds, with climate risk factors					
Median value	0.1935	0.1973	0.2010	0.1852	0.1852
Min. value	0.1935	0.1973	0.2010	0.1852	0.1852
Max. value	0.1935	0.1973	0.2010	0.1852	0.1852
Std. dev.	0.0000	0.0000	0.0000	0.0000	0.0000
Italian (C) green bonds, without climate risk factors					
Median value	0.2327	0.2173	0.2090	0.2179	0.2179
Min. value	0.2327	0.2173	0.2090	0.2179	0.2179
Max. value	0.2327	0.2173	0.2090	0.2179	0.2179
Std. dev.	0.0000	0.0000	0.0000	0.0000	0.0000
Italian (C) non-green bonds, with climate risk factors					
Median value	0.1172	0.1219	0.1270	0.1341	0.1662
Min. value	0.0542	0.0557	0.0555	0.0644	0.0556
Max. value	0.3594	0.7527	0.3502	0.3140	0.6431
Std. dev.	0.0647	0.0965	0.0611	0.0596	0.1014
Italian (C) non-green bonds, without climate risk factors					
Median value	0.1188	0.1236	0.1316	0.1359	0.1694
Min. value	0.0543	0.0557	0.0555	0.0646	0.0557
Max. value	0.4438	0.7629	0.6741	1.5836	1.5836
Std. dev.	0.0810	0.1146	0.0992	0.2149	0.2287
Dutch (C) green bonds, with climate risk factors					
Median value	0.1314	0.1316	0.1317	0.1354	0.1382
Min. value	0.1314	0.1316	0.1317	0.1354	0.1382
Max. value	0.1314	0.1316	0.1317	0.1354	0.1382
Std. dev.	0.0000	0.0000	0.0000	0.0000	0.0000

Table 51 continued

	2	6	10	45	100
Dutch (C) green bonds, without climate risk factors					
Median value	0.1317	0.1305	0.1302	0.1389	0.1410
Min. value	0.1317	0.1305	0.1302	0.1389	0.1410
Max. value	0.1317	0.1305	0.1302	0.1389	0.1410
Std. dev.	0.0000	0.0000	0.0000	0.0000	0.0000
Dutch (C) non-green bonds, with climate risk factors					
Median value	0.0800	0.0799	0.0779	0.0798	0.0777
Min. value	0.0315	0.0315	0.0315	0.0315	0.0765
Max. value	0.0857	0.0855	0.0855	0.0861	0.0873
Std. dev.	0.0210	0.0139	0.0177	0.0133	0.0039
Dutch (C) non-green bonds, without climate risk factors					
Median value	0.0804	0.0801	0.0779	0.0798	0.0779
Min. value	0.0315	0.0315	0.0315	0.0315	0.0765
Max. value	0.0856	0.0854	0.0854	0.0862	0.0873
Std. dev.	0.0211	0.0139	0.0178	0.0133	0.0039
French (C) green bonds, with climate risk factors					
Median value	0.1109	0.1111	0.1107	0.1104	0.1116
Min. value	0.1109	0.1111	0.1107	0.1104	0.1116
Max. value	0.1109	0.1111	0.1107	0.1104	0.1116
Std. dev.	0.0000	0.0000	0.0000	0.0000	0.0000

Table 51 continued

	2	6	10	45	100
French (C) green bonds, without climate risk factors					
Median value	0.1109	0.1110	0.1110	0.1106	0.1117
Min. value	0.1109	0.1110	0.1110	0.1106	0.1117
Max. value	0.1109	0.1110	0.1110	0.1106	0.1117
Std. dev.	0.0000	0.0000	0.0000	0.0000	0.0000
French (C) non-green bonds, with climate risk factors					
Median value	0.0715	0.0715	0.1033	0.0784	0.0885
Min. value	0.0707	0.0705	0.1008	0.0713	0.0715
Max. value	0.1209	0.0787	0.1059	0.1049	0.1054
Std. dev.	0.0287	0.0045	0.0036	0.0138	0.0239
French (C) non-green bonds, without climate risk factors					
Median value	0.0717	0.0718	0.1033	0.0787	0.0885
Min. value	0.0708	0.0703	0.1007	0.0714	0.0717
Max. value	0.1210	0.0788	0.1058	0.1049	0.1053
Std. dev.	0.0287	0.0046	0.0036	0.0137	0.0238
German (C) green bonds, with climate risk factors: None					
German (C) green bonds, without climate risk factors: None					
German (C) non-green bonds, with climate risk factors					
Median value	0.1042	0.1015	0.1033	0.1231	0.1266
Min. value	0.0712	0.0784	0.0306	0.0536	0.1030
Max. value	0.1689	0.1680	0.1670	0.1743	0.1689
Std. dev.	0.0312	0.0277	0.0435	0.0523	0.0334

Table 51 continued

	2	6	10	45	100
German (C) non-green bonds, without climate risk factors					
Median value	0.1042	0.1013	0.1033	0.1231	0.1268
Min. value	0.0711	0.0785	0.0306	0.0536	0.1031
Max. value	0.1774	0.1826	0.1711	0.2373	0.2448
Std. dev.	0.0329	0.0306	0.0445	0.0779	0.0759
Spanish (C) green bonds, with climate risk factors: None					
Spanish (C) green bonds, without climate risk factors: None					
Spanish (C) non-green bonds, with climate risk factors					
Median value	0.1140	0.1008	0.1041	0.1087	0.1184
Min. value	0.0777	0.0601	0.0598	0.0832	0.0739
Max. value	0.1669	0.1672	0.1811	0.3325	0.2022
Std. dev.	0.0237	0.0268	0.0296	0.0476	0.0288
Spanish (C) non-green bonds, without climate risk factors					
Median value	0.1150	0.1016	0.1046	0.1089	0.1199
Min. value	0.0781	0.0602	0.0601	0.0797	0.0733
Max. value	0.5590	0.1689	0.1916	0.6019	0.2269
Std. dev.	0.0962	0.0271	0.0306	0.0952	0.0319

Table 52 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, German government bonds (forecast horizon = 2 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
German eastw. wind (deseasonal.)	0.0035	0.0259	0.0076	0.0055
German northw. wind (deseasonal.)	0.0257	0.0180	0.0026	0.0047
German avg. temperature (deseasonal.)	−0.0060	0.0231	0.0029	0.0049
German drought SMA	0.0148	0.0285	0.0053	0.0060
German flood SMA	−0.0160	0.0148	−0.0658	0.1579
German FWI	−0.0895	0.0919	0.0047	0.0114
ΔEURIBOR	−0.0647	0.0269	−0.0530	0.0347
ΔNSS η_2	−0.0289	0.0246	−0.0065	0.0087
ΔNSS η_1	−0.0319	0.0178	−0.0133	0.0151
Log-returns of ETS carbon allowances	0.0499	0.0220	0.0025	0.0071
ΔBid-ask spread	−0.0202	0.0202	0.4793	0.5508
Log-returns of DAX index	0.0869	0.0304	0.0385	0.0124
ΔVIX	−0.0494	0.0235	−0.0118	0.0093
German GDP %change	−0.0205	0.0595	−0.0117	0.0251
German IPI %change	−0.0262	0.0339	−0.0047	0.0104
German REER %change	0.0153	0.0610	0.0153	0.0135
German Relative liquidity %change	0.0446	0.0255	0.0840	0.0885
German INFLATION RATE %change	0.0263	0.0523	−0.0087	0.0130
German Current account balance %change	0.0218	0.0561	−0.0087	0.0109
German DEBT/GDP %change	0.0017	0.0553	0.2661	0.2865
German FNW %change	−0.0194	0.0351	−0.2418	0.2168

Table 53 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, German government bonds (forecast horizon = 6 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
German eastw. wind (deseasonal.)	0.0039	0.0283	0.0077	0.0057
German northw. wind (deseasonal.)	0.0264	0.0206	0.0028	0.0049
German avg. temperature (deseasonal.)	−0.0061	0.0221	0.0030	0.0051
German drought SMA	0.0148	0.0291	0.0056	0.0061
German flood SMA	−0.0163	0.0163	−0.0637	0.1193
German FWI	−0.0928	0.0961	0.0045	0.0130
ΔEURIBOR	−0.0681	0.0253	−0.0528	0.0349
ΔNSS η_2	−0.0275	0.0260	−0.0063	0.0088
ΔNSS η_1	−0.0334	0.0202	−0.0138	0.0151
Log-returns of ETS carbon allowances	0.0488	0.0221	0.0028	0.0075
ΔBid-ask spread	−0.0215	0.0219	0.4737	0.5529
Log-returns of DAX index	0.0867	0.0315	0.0381	0.0122
ΔVIX	−0.0505	0.0256	−0.0117	0.0093
German GDP %change	−0.0197	0.0552	−0.0104	0.0187
German IPI %change	−0.0273	0.0348	−0.0059	0.0101
German REER %change	0.0054	0.0651	0.0175	0.0140
German Relative liquidity %change	0.0446	0.0258	0.1214	0.1043
German INFLATION RATE %change	0.0298	0.0526	−0.0101	0.0150
German Current account balance %change	0.0314	0.0499	−0.0089	0.0091
German DEBT/GDP %change	0.0024	0.0542	0.3892	0.3381
German FNW %change	−0.0171	0.0419	−0.3478	0.2870

Table 54 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, German government bonds (forecast horizon = 10 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
German eastw. wind (deseasonal.)	0.0002	0.0222	0.0072	0.0056
German northw. wind (deseasonal.)	0.0259	0.0199	0.0024	0.0042
German avg. temperature (deseasonal.)	−0.0018	0.0219	0.0031	0.0049
German drought SMA	0.0145	0.0253	0.0054	0.0049
German flood SMA	−0.0157	0.0137	−0.0619	0.0893
German FWI	−0.0787	0.1119	0.0045	0.0095
ΔEURIBOR	−0.0668	0.0244	−0.0533	0.0347
ΔNSS η_2	−0.0307	0.0260	−0.0064	0.0087
ΔNSS η_1	−0.0328	0.0237	−0.0143	0.0138
Log-returns of ETS carbon allowances	0.0483	0.0198	0.0023	0.0070
ΔBid-ask spread	−0.0173	0.0216	0.4786	0.5527
Log-returns of DAX index	0.0824	0.0382	0.0386	0.0120
ΔVIX	−0.0552	0.0267	−0.0114	0.0086
German GDP %change	−0.0124	0.0476	−0.0112	0.0096
German IPI %change	−0.0276	0.0327	−0.0052	0.0089
German REER %change	0.0147	0.0533	0.0166	0.0121
German Relative liquidity %change	0.0436	0.0251	0.1062	0.0936
German INFLATION RATE %change	0.0208	0.0524	−0.0099	0.0111
German Current account balance %change	0.0256	0.0481	−0.0087	0.0087
German DEBT/GDP %change	0.0084	0.0498	0.3376	0.3011
German FNW %change	−0.0178	0.0332	−0.3049	0.2569

Table 55 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, German government bonds (forecast horizon = 45 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
German eastw. wind (deseasonal.)	0.0142	0.0175	0.0069	0.0052
German northw. wind (deseasonal.)	0.0414	0.0374	0.0025	0.0039
German avg. temperature (deseasonal.)	−0.0172	0.0311	0.0027	0.0041
German drought SMA	0.0174	0.0276	0.0047	0.0051
German flood SMA	−0.0180	0.0137	−0.0653	0.0925
German FWI	−0.1631	0.1972	0.0041	0.0101
ΔEURIBOR	−0.0550	0.0234	−0.0520	0.0369
ΔNSS η_2	−0.0451	0.0321	−0.0051	0.0070
ΔNSS η_1	−0.0530	0.0412	−0.0150	0.0126
Log-returns of ETS carbon allowances	0.0431	0.0377	0.0026	0.0066
ΔBid-ask spread	−0.0207	0.0258	0.4600	0.5663
Log-returns of DAX index	0.0799	0.0379	0.0384	0.0127
ΔVIX	−0.0520	0.0253	−0.0121	0.0092
German GDP %change	−0.0112	0.0398	−0.0113	0.0092
German IPI %change	−0.0335	0.0434	−0.0060	0.0066
German REER %change	0.0068	0.1259	0.0191	0.0079
German Relative liquidity %change	0.0382	0.0134	0.1737	0.0076
German INFLATION RATE %change	−0.0161	0.1664	−0.0130	0.0069
German Current account balance %change	0.2019	0.1367	−0.0082	0.0087
German DEBT/GDP %change	0.0161	0.0311	0.5666	0.0093
German FNW %change	−0.0242	0.1876	−0.4996	0.0072

Table 56 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, German government bonds (forecast horizon = 100 days)

Regressor	Green bonds Avg. coefficient	Green bonds Avg. std	Non-green bonds Avg. coefficient	Non-green bonds Avg. std
German eastw. wind (deseasonal.)	0.0184	0.0181	0.0066	0.0051
German northw. wind (deseasonal.)	0.0580	0.0095	0.0023	0.0039
German avg. temperature (deseasonal.)	−0.0302	0.0129	0.0025	0.0033
German drought SMA	0.0191	0.0308	0.0045	0.0047
German flood SMA	−0.0179	0.0169	−0.0606	0.0937
German FWI	−0.0531	0.0399	0.0030	0.0105
ΔEURIBOR	−0.0581	0.0108	−0.0537	0.0372
ΔNSS η_2	−0.0551	0.0274	−0.0049	0.0073
ΔNSS η_1	−0.0755	0.0103	−0.0143	0.0120
Log-returns of ETS carbon allowances	0.0607	0.0111	0.0022	0.0060
ΔBid-ask spread	−0.0269	0.0168	0.4736	0.5773
Log-returns of DAX index	0.0719	0.0323	0.0378	0.0121
ΔVIX	−0.0673	0.0165	−0.0104	0.0079
German GDP %change	−0.0058	0.0250	−0.0102	0.0098
German IPI %change	−0.0216	0.0459	−0.0048	0.0062
German REER %change	−0.0491	0.0692	0.0180	0.0071
German Relative liquidity %change	0.0341	0.0254	0.1731	0.0062
German INFLATION RATE %change	0.0764	0.0230	−0.0138	0.0069
German Current account balance %change	0.1199	0.0285	−0.0094	0.0084
German DEBT/GDP %change	0.0162	0.0346	0.5665	0.0108
German FNW %change	−0.1515	0.0142	−0.4996	0.0078

Table 57 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, French government bonds (forecast horizon = 2 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
French eastw. wind (deseasonal.)	−0.0249	0.0211	0.0053	0.0064
French northw. wind (deseasonal.)	−0.0041	0.0126	0.0001	0.0027
French avg. temperature (deseasonal.)	−0.0116	0.0170	0.0121	0.0029
French drought SMA	0.0156	0.0146	0.0020	0.0039
French flood SMA	−0.0144	0.0179	−0.0143	0.0078
French FWI	−0.0002	0.0111	−0.0013	0.0053
ΔEURIBOR	−0.0507	0.0430	−0.1123	0.0524
ΔNSS η_2	−0.0002	0.0345	0.0041	0.0077
ΔNSS η_1	−0.0222	0.0184	−0.0186	0.0088
Log-returns of ETS carbon allowances	−0.0042	0.0101	−0.0085	0.0071
ΔBid-ask spread	−0.0335	0.0237	0.0176	0.0564
Log-returns of FCHI index	−0.0008	0.0166	−0.0154	0.0128
ΔVIX	0.0043	0.0163	−0.0056	0.0076
French GDP %change	−0.0601	0.0957	−0.0034	0.0109
French IPI %change	0.0237	0.0189	0.0078	0.0068
French REER %change	−0.0077	0.0188	0.0004	0.0056
French Relative liquidity %change	0.0209	0.0207	0.0195	0.0080
French INFLATION RATE %change	−0.0109	0.0139	0.0023	0.0039
French Current account balance %change	−0.0175	0.0220	0.0027	0.0025
French DEBT/GDP %change	−0.0300	0.0438	−0.0226	0.0088
French FNW %change	0.0227	0.0226	−0.0177	0.0051

Table 58 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, French government bonds (forecast horizon = 6 days)

Regressor	Green bonds Avg. coefficient	Green bonds Avg. std	Non-green bonds Avg. coefficient	Non-green bonds Avg. std
French eastw. wind (deseasonal.)	−0.0239	0.0203	0.0053	0.0065
French northw. wind (deseasonal.)	−0.0041	0.0123	0.0001	0.0027
French avg. temperature (deseasonal.)	−0.0113	0.0178	0.0121	0.0029
French drought SMA	0.0162	0.0156	0.0019	0.0040
French flood SMA	−0.0150	0.0194	−0.0143	0.0078
French FWI	0.0004	0.0125	−0.0013	0.0053
ΔEURIBOR	−0.0495	0.0427	−0.1121	0.0524
ΔNSS η_2	0.0025	0.0333	0.0041	0.0077
ΔNSS η_1	−0.0232	0.0175	−0.0186	0.0088
Log-returns of ETS carbon allowances	−0.0029	0.0093	−0.0085	0.0071
ΔBid-ask spread	−0.0357	0.0209	0.0167	0.0554
Log-returns of FCHI index	−0.0011	0.0167	−0.0154	0.0128
ΔVIX	0.0038	0.0168	−0.0056	0.0077
French GDP %change	−0.0610	0.0995	−0.0034	0.0110
French IPI %change	0.0236	0.0201	0.0079	0.0065
French REER %change	−0.0077	0.0189	0.0004	0.0056
French Relative liquidity %change	0.0222	0.0254	0.0196	0.0081
French INFLATION RATE %change	−0.0113	0.0142	0.0023	0.0039
French Current account balance %change	−0.0182	0.0206	0.0027	0.0025
French DEBT/GDP %change	−0.0306	0.0467	−0.0227	0.0089
French FNW %change	0.0236	0.0206	−0.0177	0.0050

Table 59 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, French government bonds (forecast horizon = 10 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
French eastw. wind (deseasonal.)	−0.0258	0.0237	0.0054	0.0065
French northw. wind (deseasonal.)	−0.0062	0.0149	0.0001	0.0027
French avg. temperature (deseasonal.)	−0.0128	0.0183	0.0122	0.0029
French drought SMA	0.0169	0.0171	0.0020	0.0039
French flood SMA	−0.0131	0.0141	−0.0143	0.0078
French FWI	−0.0006	0.0114	−0.0013	0.0053
ΔEURIBOR	−0.0499	0.0432	−0.1130	0.0523
ΔNSS η_2	0.0016	0.0288	0.0042	0.0077
ΔNSS η_1	−0.0238	0.0165	−0.0185	0.0087
Log-returns of ETS carbon allowances	−0.0053	0.0077	−0.0086	0.0071
ΔBid-ask spread	−0.0344	0.0264	0.0170	0.0541
Log-returns of FCHI index	−0.0022	0.0159	−0.0155	0.0128
ΔVIX	0.0052	0.0173	−0.0055	0.0077
French GDP %change	−0.0580	0.0988	−0.0034	0.0111
French IPI %change	0.0228	0.0127	0.0079	0.0066
French REER %change	−0.0073	0.0167	0.0005	0.0055
French Relative liquidity %change	0.0187	0.0125	0.0196	0.0081
French INFLATION RATE %change	−0.0110	0.0149	0.0023	0.0039
French Current account balance %change	−0.0175	0.0250	0.0027	0.0026
French DEBT/GDP %change	−0.0286	0.0382	−0.0227	0.0090
French FNW %change	0.0244	0.0293	−0.0178	0.0049

Table 60 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, French government bonds (forecast horizon = 45 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
French eastw. wind (deseasonal.)	−0.0231	0.0253	0.0057	0.0070
French northw. wind (deseasonal.)	−0.0057	0.0132	0.0001	0.0030
French avg. temperature (deseasonal.)	−0.0124	0.0179	0.0122	0.0030
French drought SMA	0.0135	0.0182	0.0019	0.0042
French flood SMA	−0.0131	0.0155	−0.0143	0.0083
French FWI	0.0011	0.0096	−0.0010	0.0057
ΔEURIBOR	−0.0598	0.0498	−0.1145	0.0556
ΔNSS η_2	0.0103	0.0373	0.0048	0.0079
ΔNSS η_1	−0.0239	0.0176	−0.0181	0.0092
Log-returns of ETS carbon allowances	−0.0023	0.0068	−0.0085	0.0074
ΔBid-ask spread	−0.0418	0.0143	0.0154	0.0457
Log-returns of FCHI index	0.0021	0.0148	−0.0158	0.0129
ΔVIX	0.0091	0.0090	−0.0054	0.0084
French GDP %change	−0.0460	0.0771	−0.0034	0.0112
French IPI %change	0.0247	0.0140	0.0074	0.0067
French REER %change	−0.0066	0.0175	0.0002	0.0058
French Relative liquidity %change	0.0287	0.0414	0.0195	0.0081
French INFLATION RATE %change	−0.0060	0.0167	0.0022	0.0041
French Current account balance %change	−0.0240	0.0285	0.0028	0.0027
French DEBT/GDP %change	−0.0304	0.0425	−0.0222	0.0089
French FNW %change	0.0213	0.0237	−0.0181	0.0049

Table 61 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, French government bonds (forecast horizon = 100 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
French eastw. wind (deseasonal.)	−0.0242	0.0283	0.0069	0.0078
French northw. wind (deseasonal.)	−0.0005	0.0033	0.0005	0.0028
French avg. temperature (deseasonal.)	0.0036	0.0100	0.0117	0.0027
French drought SMA	0.0105	0.0122	0.0024	0.0039
French flood SMA	−0.0270	0.0262	−0.0138	0.0077
French FWI	0.0063	0.0033	−0.0002	0.0060
ΔEURIBOR	−0.0513	0.0498	−0.1153	0.0483
ΔNSS η_2	−0.0110	0.0502	0.0059	0.0081
ΔNSS η_1	−0.0233	0.0200	−0.0170	0.0084
Log-returns of ETS carbon allowances	0.0001	0.0104	−0.0093	0.0064
ΔBid-ask spread	−0.0315	0.0304	0.0165	0.0474
Log-returns of FCHI index	0.0006	0.0114	−0.0163	0.0134
ΔVIX	0.0167	0.0114	−0.0049	0.0083
French GDP %change	−0.0127	0.0143	−0.0056	0.0121
French IPI %change	0.0260	0.0132	0.0087	0.0074
French REER %change	−0.0099	0.0062	0.0012	0.0059
French Relative liquidity %change	0.0160	0.0052	0.0211	0.0087
French INFLATION RATE %change	0.0012	0.0045	0.0025	0.0044
French Current account balance %change	−0.0031	0.0139	0.0029	0.0025
French DEBT/GDP %change	−0.0195	0.0119	−0.0246	0.0102
French FNW %change	0.0269	0.0312	−0.0175	0.0045

Table 62 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Spanish government bonds (forecast horizon = 2 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Spanish eastw. wind (deseasonal.)	−0.0353	0.0264	0.0025	0.0073
Spanish northw. wind (deseasonal.)	−0.0674	0.0409	0.0063	0.0075
Spanish avg. temperature (deseasonal.)	−0.0160	0.0498	0.0038	0.0075
Spanish drought SMA	– –	–	0.0046	0.0216
Spanish flood SMA	−0.0966	0.0817	0.0073	0.0740
Spanish FWI	−0.1319	0.0807	−0.0042	0.0081
ΔEURIBOR	0.0228	0.0213	−0.0049	0.0486
ΔNSS η_2	−0.0341	0.0414	−0.0105	0.0111
ΔNSS η_1	−0.0005	0.0319	−0.0165	0.0219
Log-returns of ETS carbon allowances	0.0519	0.0508	0.0028	0.0071
ΔBid-ask spread	−0.0090	0.0163	0.0557	0.3461
Log-returns of IBEX index	0.0334	0.0287	−0.0212	0.0128
ΔVIX	0.0030	0.0324	−0.0055	0.0123
Spanish GDP %change	0.0715	0.1219	0.0081	0.0169
Spanish IPI %change	−0.0696	0.0639	−0.0066	0.0104
Spanish REER %change	−0.0839	0.0991	0.0042	0.0094
Spanish Relative liquidity %change	0.0601	0.1174	−0.0012	0.0102
Spanish INFLATION RATE %change	0.0361	0.0966	−0.0004	0.0101
Spanish Current account balance %change	−0.0158	0.0279	0.0191	0.0507
Spanish DEBT/GDP %change	0.1311	0.3138	−0.0002	0.0221
Spanish FNW %change	0.1233	0.3101	−0.0150	0.0303

Table 63 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Spanish government bonds (forecast horizon = 6 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Spanish eastw. wind (deseasonal.)	−0.0346	0.0214	0.0028	0.0066
Spanish northw. wind (deseasonal.)	−0.0596	0.0432	0.0069	0.0068
Spanish avg. temperature (deseasonal.)	−0.0256	0.0539	0.0044	0.0069
Spanish drought SMA	−−	–	0.0067	0.0224
Spanish flood SMA	−0.0974	0.0874	0.0035	0.0645
Spanish FWI	−0.1418	0.0891	−0.0026	0.0073
ΔEURIBOR	0.0232	0.0187	−0.0122	0.0504
ΔNSS η_2	−0.0431	0.0412	−0.0096	0.0102
ΔNSS η_1	−0.0107	0.0408	−0.0185	0.0216
Log-returns of ETS carbon allowances	0.0435	0.0547	0.0022	0.0067
ΔBid-ask spread	−0.0077	0.0144	0.0816	0.4371
Log-returns of IBEX index	0.0385	0.0367	−0.0256	0.0123
ΔVIX	−0.0010	0.0308	−0.0002	0.0111
Spanish GDP %change	0.0778	0.1175	0.0050	0.0130
Spanish IPI %change	−0.0714	0.0729	−0.0076	0.0098
Spanish REER %change	−0.0726	0.1028	0.0036	0.0090
Spanish Relative liquidity %change	0.0682	0.1305	−0.0010	0.0100
Spanish INFLATION RATE %change	0.0249	0.0991	−0.0001	0.0092
Spanish Current account balance %change	−0.0235	0.0312	0.0265	0.0448
Spanish DEBT/GDP %change	0.1335	0.2734	−0.0009	0.0173
Spanish FNW %change	0.1242	0.2700	−0.0178	0.0255

Table 64 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Spanish government bonds (forecast horizon = 10 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Spanish eastw. wind (deseasonal.)	−0.0249	0.0279	0.0027	0.0064
Spanish northw. wind (deseasonal.)	−0.0644	0.0526	0.0069	0.0070
Spanish avg. temperature (deseasonal.)	−0.0162	0.0496	0.0045	0.0071
Spanish drought SMA	−−	–	0.0067	0.0219
Spanish flood SMA	−0.0990	0.1121	0.0058	0.0673
Spanish FWI	−0.1120	0.0613	−0.0025	0.0071
ΔEURIBOR	0.0198	0.0204	−0.0124	0.0509
ΔNSS η_2	−0.0420	0.0484	−0.0092	0.0103
ΔNSS η_1	−0.0096	0.0497	−0.0178	0.0221
Log-returns of ETS carbon allowances	0.0486	0.0570	0.0021	0.0064
ΔBid-ask spread	−0.0029	0.0120	0.0850	0.4384
Log-returns of IBEX index	0.0441	0.0453	−0.0257	0.0123
ΔVIX	−0.0044	0.0360	0.0000	0.0111
Spanish GDP %change	0.0668	0.0947	0.0060	0.0135
Spanish IPI %change	−0.0664	0.0610	−0.0077	0.0096
Spanish REER %change	−0.0948	0.1367	0.0034	0.0090
Spanish Relative liquidity %change	0.0303	0.0645	−0.0009	0.0102
Spanish INFLATION RATE %change	0.0288	0.1055	−0.0003	0.0088
Spanish Current account balance %change	−0.0249	0.0319	0.0263	0.0456
Spanish DEBT/GDP %change	0.1146	0.2856	0.0003	0.0185
Spanish FNW %change	0.0953	0.3182	−0.0160	0.0263

Table 65 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Spanish government bonds (forecast horizon = 45 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Spanish eastw. wind (deseasonal.)	−0.0164	0.0211	0.0029	0.0061
Spanish northw. wind (deseasonal.)	−0.0045	0.1172	0.0062	0.0067
Spanish avg. temperature (deseasonal.)	−0.0354	0.0537	0.0046	0.0061
Spanish drought SMA	−−	–	0.0063	0.0243
Spanish flood SMA	−0.1709	0.1532	0.0013	0.0620
Spanish FWI	−0.0713	0.0945	−0.0023	0.0069
ΔEURIBOR	0.0515	0.0270	−0.0132	0.0503
ΔNSS η_2	−0.0256	0.0493	−0.0098	0.0100
ΔNSS η_1	−0.0230	0.0351	−0.0185	0.0186
Log-returns of ETS carbon allowances	−0.0067	0.0806	0.0016	0.0061
ΔBid-ask spread	0.0010	0.0549	0.0774	0.4292
Log-returns of IBEX index	−0.0184	0.0634	−0.0267	0.0109
ΔVIX	−0.0604	0.0433	−0.0008	0.0109
Spanish GDP %change	0.0376	0.0646	0.0062	0.0129
Spanish IPI %change	−0.0924	0.0352	−0.0086	0.0092
Spanish REER %change	−0.2689	0.2282	0.0032	0.0090
Spanish Relative liquidity %change	0.0097	0.1325	0.0002	0.0112
Spanish INFLATION RATE %change	0.1321	0.2498	−0.0011	0.0082
Spanish Current account balance %change	−0.0214	0.0308	0.0179	0.0322
Spanish DEBT/GDP %change	0.0180	0.3972	0.0012	0.0171
Spanish FNW %change	0.0219	0.5594	−0.0144	0.0240

Table 66 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Spanish government bonds (forecast horizon = 100 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Spanish eastw. wind (deseasonal.)	−0.0002	0.0052	0.0029	0.0051
Spanish northw. wind (deseasonal.)	−0.0568	0.0852	0.0055	0.0059
Spanish avg. temperature (deseasonal.)	−0.1097	0.0285	0.0056	0.0051
Spanish drought SMA	– –	–	0.0076	0.0251
Spanish flood SMA	−0.0780	0.0637	0.0108	0.0634
Spanish FWI	−0.1533	0.0319	−0.0021	0.0064
ΔEURIBOR	0.0420	0.0304	−0.0138	0.0526
ΔNSS η_2	0.0076	0.0311	−0.0089	0.0081
ΔNSS η_1	−0.0115	0.0690	−0.0180	0.0165
Log-returns of ETS carbon allowances	0.0083	0.1240	0.0013	0.0058
ΔBid-ask spread	0.0206	0.0410	0.0751	0.4537
Log-returns of IBEX index	0.0167	0.0465	−0.0270	0.0117
ΔVIX	−0.0115	0.0498	0.0016	0.0106
Spanish GDP %change	0.0400	0.0081	0.0048	0.0114
Spanish IPI %change	−0.0857	0.0159	−0.0079	0.0094
Spanish REER %change	−0.0645	0.1043	0.0020	0.0095
Spanish Relative liquidity %change	0.3187	0.2300	0.0016	0.0131
Spanish INFLATION RATE %change	0.0631	0.0372	0.0012	0.0079
Spanish Current account balance %change	0.0008	0.0052	0.0170	0.0271
Spanish DEBT/GDP %change	−0.2951	0.6399	0.0016	0.0118
Spanish FNW %change	0.0220	0.1772	−0.0145	0.0201

Table 67 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Italian government bonds (forecast horizon = 2 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Italian eastw. wind (deseasonal.)	−0.0463	0.0371	−0.0037	0.0109
Italian northw. wind (deseasonal.)	0.0925	0.0368	0.0065	0.0117
Italian avg. temperature (deseasonal.)	0.0063	0.0353	−0.0031	0.0104
Italian drought SMA	−0.0049	0.0627	0.0252	0.0298
Italian flood SMA	0.0909	0.0628	0.1472	0.1900
Italian FWI	0.1007	0.0980	−0.0027	0.0124
ΔEURIBOR	0.0372	0.0870	0.0209	0.0487
ΔNSS η_2	−0.0232	0.0406	−0.0099	0.0166
ΔNSS η_1	−0.1037	0.0370	−0.0151	0.0230
Log-returns of ETS carbon allowances	0.0622	0.0571	0.0055	0.0133
ΔBid-ask spread	0.0351	0.0599	0.0640	0.3224
Log-returns of FTSE MIB index	0.1484	0.0935	−0.0110	0.0188
ΔVIX	−0.0302	0.0575	−0.0018	0.0209
Italian GDP %change	−0.0240	0.0302	0.0228	0.0563
Italian IPI %change	0.0005	0.0060	−0.0100	0.0174
Italian REER %change	−0.0064	0.0103	0.0014	0.0133
Italian Relative liquidity %change	−0.0224	0.0343	−0.0060	0.0151
Italian INFLATION RATE %change	−0.0127	0.0810	−0.0020	0.0157
Italian Current account balance %change	0.0243	0.0487	−0.0058	0.0192
Italian DEBT/GDP %change	−1.4391	1.5269	−0.0169	0.0462
Italian FNW %change	0.8632	1.1048	−0.0202	0.1693

Appendix D Scenario analysis

In line with the Fit-for-55 Scenario Analysis Exercise, the last available values of 2022 are selected as the starting bond prices and spreads. The shifts are computed as the changes after 1 year from the initial starting values. The ARIMAX(p,d,q) equation of each bond spread is used to derive daily projections until the end of 2023, i.e.

$$\left(1-\sum_{i=1}^{p}\hat{\varphi}_{b,i}L^{i}\right)(1-L)^{d}s_{b,t+1}=\hat{\theta}_{b,0}+\left(1+\sum_{j=1}^{q}\hat{\theta}_{b,j}L^{j}\right)\epsilon_{b,t+1}+\sum_{k=1}^{n}\hat{\alpha}_{b,k}X_{b,k,t}, \tag{D2}$$

where the coefficient values $\varphi_{b,i}, \theta_{b,0}, \theta_{b,j}, \alpha_{b,k}$ are replaced by their estimates $\hat{\varphi}_{b,i}, \hat{\theta}_{b,0}, \hat{\theta}_{b,j}, \hat{\alpha}_{b,k}$, for $i = 1, ..., p$, $j = 1, ..., q$, and $k = 1, ..., n$. This can be done by either performing multiple simulations and then averaging over all paths, or by computing the conditional expected value of the process given the input regressors. We attempt both versions and find that, already when the number of simulations exceed 1000, the two methods converge. Finally, once the daily spread increments are found for the entire year of 2023, they are summed to obtain the year-end change.

The projections of temperature and wind speed are downloaded from the Copernicus Data Store, using dataset *Climate and energy related variables from the Pan-European Climate Database derived from reanalysis and climate projections* (scenario SSP2-4.5, the closest to the NGFS NDC scenario). The Fire Weather Index projections are downloaded from the *Fire danger indicators for Europe from 1970 to 2098 derived from climate projections* dataset (scenario RCP 2.6, the closest to the NGFS NDC scenario). The realized Soil Moisture Anomaly index of 2023 is downloaded from the European Drought Observatory, as the forecasts for 2023 are no longer available at the time of this analysis. The time series of wind and temperature projections are deseasonalized just as in the original model. As for the macro-economic regressors, the technical document by the European Systemic Risk Board (2023) provides country-level shocks to inflation (HICP), GDP, Euro area risk free rate yields, and equity (which we use, taking their cross-sector mean, for the country-specific stock market index), under each scenario. As the shocks are assumed to refer to a time-frame of length one year but the ARIMAX model requires daily values, they are divided by 260, the number of business days in 2023, before being included in the model. The remaining regressors, if no scenario projection is available, are set to their historical average value.

Additionally, as the input variables of the model had been standardized in order to facilitate estimator convergence and coefficient comparability in the in-sample portion of this work, the same standardizing quantities that were used in the model fit phase (mean and standard deviation) are applied to the new regressors, to ensure consistency in their scale. As a consequence, the spread increments that are the output of the model are also standardized. They are therefore converted back to their original scale by using the same means and standard deviations of the model fit phase. Finally, they are classified by bond maturity, averaged and reported in Table 43.

Table 68 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Italian government bonds (forecast horizon = 6 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Italian eastw. wind (deseasonal.)	−0.0628	0.0267	−0.0040	0.0105
Italian northw. wind (deseasonal.)	0.0889	0.0284	0.0056	0.0111
Italian avg. temperature (deseasonal.)	−0.0088	0.0377	−0.0033	0.0105
Italian drought SMA	0.0005	0.0697	0.0258	0.0301
Italian flood SMA	0.0564	0.0717	0.1481	0.1912
Italian FWI	0.1136	0.1335	−0.0016	0.0108
ΔEURIBOR	−0.0060	0.0699	0.0223	0.0494
ΔNSS η_2	−0.0197	0.0365	−0.0097	0.0164
ΔNSS η_1	−0.0943	0.0373	−0.0158	0.0238
Log-returns of ETS carbon allowances	0.0851	0.0464	0.0059	0.0133
ΔBid-ask spread	0.0364	0.0627	0.0622	0.3230
Log-returns of FTSE MIB index	0.1089	0.1049	−0.0112	0.0188
ΔVIX	−0.0338	0.0624	−0.0026	0.0217
Italian GDP %change	−0.0224	0.0320	0.0210	0.0550
Italian IPI %change	0.0006	0.0061	−0.0094	0.0180
Italian REER %change	−0.0066	0.0104	0.0012	0.0135
Italian Relative liquidity %change	−0.0220	0.0348	−0.0060	0.0150
Italian INFLATION RATE %change	−0.0142	0.0914	−0.0014	0.0158
Italian Current account balance %change	0.0169	0.0341	−0.0042	0.0178
Italian DEBT/GDP %change	−1.6611	2.0054	−0.0166	0.0459
Italian FNW %change	1.0123	1.4253	0.0088	0.1026

Table 69 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Italian government bonds (forecast horizon = 10 days)

	Green bonds		Non-green bonds	
Regulator	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Italian eastw. wind (deseasonal.)	−0.0475	0.0323	−0.0036	0.0105
Italian northw. wind (deseasonal.)	0.1044	0.0474	0.0068	0.0129
Italian avg. temperature (deseasonal.)	−0.0125	0.0590	−0.0040	0.0100
Italian drought SMA	−0.0176	0.0902	0.0251	0.0303
Italian flood SMA	0.0668	0.1400	0.1476	0.1887
Italian FWI	0.1144	0.0877	−0.0034	0.0137
ΔEURIBOR	0.0387	0.0185	0.0229	0.0490
ΔNSS η_2	−0.0394	0.0287	−0.0102	0.0167
ΔNSS η_1	−0.1159	0.0524	−0.0154	0.0245
Log-returns of ETS carbon allowances	0.0675	0.0949	0.0051	0.0123
ΔBid-ask spread	0.0474	0.0635	0.0649	0.3251
Log-returns of FTSE MIB index	0.1770	0.0861	−0.0104	0.0188
ΔVIX	−0.0168	0.0381	−0.0020	0.0207
Italian GDP %change	−0.0229	0.0309	0.0191	0.0476
Italian IPI %change	0.0013	0.0065	−0.0096	0.0173
Italian REER %change	−0.0071	0.0108	0.0016	0.0133
Italian Relative liquidity %change	−0.0219	0.0339	−0.0058	0.0148
Italian INFLATION RATE %change	−0.0290	0.0428	−0.0033	0.0161
Italian Current account balance %change	0.0176	0.0397	−0.0057	0.0211
Italian DEBT/GDP %change	−0.9162	1.3386	−0.0172	0.0387
Italian FNW %change	0.5045	0.9786	−0.0707	0.1919

Table 70 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Italian government bonds (forecast horizon = 45 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Italian eastw. wind (deseasonal.)	−0.0645	0.0100	−0.0023	0.0066
Italian northw. wind (deseasonal.)	0.0800	0.0050	0.0031	0.0075
Italian avg. temperature (deseasonal.)	−0.0531	0.0057	−0.0058	0.0068
Italian drought SMA	−0.0800	0.0070	0.0252	0.0306
Italian flood SMA	−0.0319	0.0049	0.1549	0.1975
Italian FWI	0.1672	0.0115	−0.0009	0.0099
ΔEURIBOR	0.0355	0.0262	0.0246	0.0455
ΔNSS η_2	−0.0420	0.0116	−0.0107	0.0147
ΔNSS η_1	−0.0839	0.0107	−0.0108	0.0151
Log-returns of ETS carbon allowances	0.1316	0.0041	0.0058	0.0087
ΔBid-ask spread	0.0151	0.0221	0.0615	0.3223
Log-returns of FTSE MIB index	0.1334	0.0248	−0.0112	0.0132
ΔVIX	−0.0035	0.0202	−0.0040	0.0158
Italian GDP %change	−0.0069	0.0307	0.0695	0.0241
Italian IPI %change	0.0027	0.0061	−0.0075	0.0117
Italian REER %change	−0.0119	0.0049	0.0015	0.0130
Italian Relative liquidity %change	−0.0237	0.0359	−0.0059	0.0155
Italian INFLATION RATE %change	−0.0515	0.0030	−0.0018	0.0086
Italian Current account balance %change	0.0284	0.0280	−0.0040	0.0132
Italian DEBT/GDP %change	0.2845	0.0159	−0.0506	0.0159
Italian FNW %change	−0.1722	0.0193	0.1041	0.0269

Table 71 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Italian government bonds (forecast horizon = 100 days)

Regulator	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Italian eastw. wind (deseasonal.)	−0.0577	0.0092	−0.0016	0.0064
Italian northw. wind (deseasonal.)	0.0849	0.0011	0.0029	0.0075
Italian avg. temperature (deseasonal.)	−0.0565	0.0006	−0.0057	0.0066
Italian drought SMA	−0.0856	0.0049	0.0253	0.0343
Italian flood SMA	−0.0335	0.0068	0.1709	0.2154
Italian FWI	0.1714	0.0005	−0.0009	0.0099
ΔEURIBOR	0.0159	0.0229	0.0229	0.0478
ΔNSS η_2	−0.0465	0.0163	−0.0087	0.0141
ΔNSS η_1	−0.0863	0.0145	−0.0116	0.0161
Log-returns of ETS carbon allowances	0.1379	0.0036	0.0050	0.0088
ΔBid-ask spread	0.0057	0.0318	0.0297	0.3097
Log-returns of FTSE MIB index	0.1490	0.0050	−0.0104	0.0130
ΔVIX	0.0040	0.0080	−0.0019	0.0168
Italian GDP %change	0.0115	0.0376	0.0037	0.0219
Italian IPI %change	0.0019	0.0090	−0.0082	0.0120
Italian REER %change	−0.0148	0.0053	0.0023	0.0127
Italian Relative liquidity %change	−0.0367	0.0638	−0.0045	0.0154
Italian INFLATION RATE %change	−0.0483	0.0005	−0.0017	0.0087
Italian Current account balance %change	0.0209	0.0374	−0.0025	0.0126
Italian DEBT/GDP %change	0.2946	0.0246	−0.0074	0.0137
Italian FNW %change	−0.1867	0.0182	−0.0212	0.0226

Table 72 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Dutch government bonds (forecast horizon = 2 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Dutch eastw. wind (deseasonal.)	0.0219	0.0236	0.0073	0.0040
Dutch northw. wind (deseasonal.)	0.0159	0.0156	0.0053	0.0034
Dutch avg. temperature (deseasonal.)	−0.0126	0.0140	−0.0032	0.0042
Dutch drought SMA	0.0332	0.0169	0.0046	0.0033
Dutch flood SMA	0.0162	0.0125	−0.0017	0.0045
Dutch FWI	−0.0001	0.0249	0.0061	0.0080
ΔEURIBOR	−0.0568	0.0962	−0.0515	0.0359
ΔNSS η_2	−0.0036	0.0217	−0.0030	0.0078
ΔNSS η_1	−0.0034	0.0302	−0.0127	0.0117
Log-returns of ETS carbon allowances	0.0053	0.0171	−0.0036	0.0063
ΔBid-ask spread	0.0158	0.0208	−0.0064	0.0389
Log-returns of AEX index	−0.0197	0.0210	0.0154	0.0101
ΔVIX	−0.0492	0.0207	−0.0083	0.0072
Dutch GDP %change	−0.0125	0.0114	−0.0026	0.0120
Dutch IPI %change	−0.0327	0.0214	−0.0142	0.0088
Dutch REER %change	0.0491	0.0250	0.0083	0.0067
Dutch Relative liquidity %change	0.0344	0.0338	0.0093	0.0073
Dutch INFLATION RATE %change	−0.0531	0.0211	−0.0088	0.0086
Dutch Current account balance %change	0.0179	0.0153	0.0386	0.0649
Dutch DEBT/GDP %change	−0.0219	0.0216	−0.0042	0.0094
Dutch FNW %change	−0.0353	0.0179	−0.0151	0.0095

Table 73 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Dutch government bonds (forecast horizon = 6 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Dutch eastw. wind (deseasonal.)	0.0217	0.0234	0.0073	0.0040
Dutch northw. wind (deseasonal.)	0.0159	0.0166	0.0053	0.0034
Dutch avg. temperature (deseasonal.)	−0.0112	0.0141	−0.0031	0.0043
Dutch drought SMA	0.0326	0.0174	0.0046	0.0033
Dutch flood SMA	0.0165	0.0139	−0.0017	0.0045
Dutch FWI	−0.0006	0.0246	0.0062	0.0080
ΔEURIBOR	−0.0628	0.1115	−0.0518	0.0358
ΔNSS η_2	−0.0052	0.0214	−0.0030	0.0078
ΔNSS η_1	−0.0025	0.0285	−0.0128	0.0116
Log-returns of ETS carbon allowances	0.0043	0.0168	−0.0035	0.0064
ΔBid-ask spread	0.0128	0.0221	−0.0062	0.0391
Log-returns of AEX index	−0.0170	0.0216	0.0154	0.0102
ΔVIX	−0.0478	0.0210	−0.0083	0.0073
Dutch GDP %change	−0.0117	0.0117	−0.0026	0.0121
Dutch IPI %change	−0.0337	0.0242	−0.0141	0.0089
Dutch REER %change	0.0497	0.0274	0.0083	0.0069
Dutch Relative liquidity %change	0.0334	0.0320	0.0094	0.0073
Dutch INFLATION RATE %change	−0.0531	0.0203	−0.0086	0.0085
Dutch Current account balance %change	0.0184	0.0160	0.0380	0.0640
Dutch DEBT/GDP %change	−0.0206	0.0196	−0.0042	0.0096
Dutch FNW %change	−0.0356	0.0188	−0.0151	0.0094

Table 74 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Dutch government bonds (forecast horizon = 10 days)

Regressor	Green bonds		Non-green bonds	
	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Dutch eastw. wind (deseasonal.)	0.0204	0.0248	0.0075	0.0040
Dutch northw. wind (deseasonal.)	0.0138	0.0153	0.0054	0.0034
Dutch avg. temperature (deseasonal.)	−0.0157	0.0126	−0.0033	0.0043
Dutch drought SMA	0.0307	0.0134	0.0045	0.0034
Dutch flood SMA	0.0131	0.0091	−0.0019	0.0044
Dutch FWI	0.0017	0.0217	0.0065	0.0080
ΔEURIBOR	−0.0554	0.0818	−0.0530	0.0363
ΔNSS η_2	−0.0011	0.0233	−0.0030	0.0078
ΔNSS η_1	−0.0015	0.0351	−0.0130	0.0116
Log-returns of ETS carbon allowances	0.0061	0.0171	−0.0037	0.0063
ΔBid-ask spread	0.0176	0.0213	−0.0066	0.0385
Log-returns of AEX index	−0.0255	0.0198	0.0155	0.0100
ΔVIX	−0.0544	0.0157	−0.0082	0.0072
Dutch GDP %change	−0.0130	0.0112	−0.0029	0.0116
Dutch IPI %change	−0.0267	0.0143	−0.0141	0.0089
Dutch REER %change	0.0435	0.0189	0.0084	0.0065
Dutch Relative liquidity %change	0.0329	0.0320	0.0093	0.0069
Dutch INFLATION RATE %change	−0.0502	0.0177	−0.0088	0.0086
Dutch Current account balance %change	0.0155	0.0124	0.0395	0.0622
Dutch DEBT/GDP %change	−0.0254	0.0234	−0.0044	0.0090
Dutch FNW %change	−0.0307	0.0138	−0.0150	0.0097

Table 75 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Dutch government bonds (forecast horizon = 45 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Dutch eastw. wind (deseasonal.)	0.0226	0.0252	0.0074	0.0042
Dutch northw. wind (deseasonal.)	0.0082	0.0124	0.0053	0.0034
Dutch avg. temperature (deseasonal.)	−0.0162	0.0103	−0.0030	0.0042
Dutch drought SMA	0.0274	0.0114	0.0045	0.0036
Dutch flood SMA	0.0110	0.0061	−0.0018	0.0044
Dutch FWI	0.0063	0.0194	0.0062	0.0077
ΔEURIBOR	−0.0684	0.1055	−0.0542	0.0374
ΔNSS η_2	−0.0068	0.0147	−0.0029	0.0078
ΔNSS η_1	0.0170	0.0394	−0.0123	0.0121
Log-returns of ETS carbon allowances	0.0064	0.0143	−0.0036	0.0065
ΔBid-ask spread	0.0144	0.0178	−0.0062	0.0384
Log-returns of AEX index	−0.0291	0.0101	0.0149	0.0106
ΔVIX	−0.0491	0.0191	−0.0080	0.0074
Dutch GDP %change	−0.0132	0.0079	−0.0030	0.0117
Dutch IPI %change	−0.0228	0.0056	−0.0138	0.0084
Dutch REER %change	0.0368	0.0118	0.0087	0.0069
Dutch Relative liquidity %change	0.0291	0.0269	0.0093	0.0074
Dutch INFLATION RATE %change	−0.0437	0.0136	−0.0084	0.0090
Dutch Current account balance %change	0.0143	0.0078	0.0358	0.0647
Dutch DEBT/GDP %change	−0.0243	0.0171	−0.0039	0.0087
Dutch FNW %change	−0.0240	0.0081	−0.0154	0.0104

Table 76 Average coefficient and standard deviation of exogenous regressors, rolling-window estimation, Dutch government bonds (forecast horizon = 100 days)

	Green bonds		Non-green bonds	
Regressor	Avg. coefficient	Avg. std	Avg. coefficient	Avg. std
Dutch eastw. wind (deseasonal.)	0.0217	0.0216	0.0073	0.0041
Dutch northw. wind (deseasonal.)	0.0137	0.0128	0.0052	0.0034
Dutch avg. temperature (deseasonal.)	−0.0140	0.0127	−0.0034	0.0040
Dutch drought SMA	0.0274	0.0083	0.0042	0.0032
Dutch flood SMA	0.0100	0.0046	−0.0020	0.0040
Dutch FWI	0.0027	0.0164	0.0063	0.0073
ΔEURIBOR	−0.1040	0.1230	−0.0538	0.0366
ΔNSS η_2	−0.0015	0.0198	−0.0028	0.0073
ΔNSS η_1	0.0120	0.0757	−0.0115	0.0121
Log-returns of ETS carbon allowances	0.0013	0.0207	−0.0040	0.0061
ΔBid-ask spread	0.0151	0.0248	−0.0060	0.0329
Log-returns of AEX index	−0.0324	0.0134	0.0147	0.0110
ΔVIX	−0.0479	0.0222	−0.0080	0.0080
Dutch GDP %change	−0.0088	0.0112	−0.0037	0.0139
Dutch IPI %change	−0.0210	0.0036	−0.0133	0.0085
Dutch REER %change	0.0389	0.0096	0.0085	0.0068
Dutch Relative liquidity %change	0.0326	0.0281	0.0096	0.0069
Dutch INFLATION RATE %change	−0.0397	0.0140	−0.0078	0.0077
Dutch Current account balance %change	0.0135	0.0118	0.0369	0.0569
Dutch DEBT/GDP %change	−0.0266	0.0201	−0.0045	0.0084
Dutch FNW %change	−0.0232	0.0139	−0.0151	0.0097

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Data Availability All data, except for financial data coming from the platform Refinitiv Datastream, is free to download from the sources mentioned in Section 4.1. The download of the financial data from Refinitiv Datastream is subject to the acquisition of a license.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

Code availability The code is available upon request.

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