Energy Economics 149 (2025) 108664

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

A climate risk hedge? Investigating the exposure of green and non-green corporate bonds to climate risk

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ARTICLE INFO

JEL classification:
C50
C58
G01
G10
G12
Q50

Keywords:
Green bonds
Climate risk
Physical risk
Transition risk
Credit risk
Carbon allowances

ABSTRACT

We perform an in-depth analysis of climate risk in the corporate bond market, focusing on the green-bond issuers of the three largest European Union economies by GDP: Germany, France, and Italy. We do so by evaluating the impact, on the spreads of their green and non-green bonds, of a number of potential physical risk drivers, selected in line with the ECB climate stress tests and the extant literature, and through the fitting of ARIMAX models. Additionally, we include the log-returns of EU carbon allowances as a potential proxy of transition risk. We find that green and non-green bonds of the same issuer can differ in their exposure to the physical risk variables. Depending on the issuer, green bonds can be equally or less exposed than their non-green counterparts. Additionally, multiple firms in the renewable energy sector have green bonds which provide protection against physical risk. EU carbon allowances are not found to have a consistently significant impact on bond spreads. In line with these findings, we propose an extension of an intensity-based (reduced-form) credit risk model and assess its ability to describe and fit the bond data.

1. Introduction

Climate risk measurement research is rapidly expanding, attracting growing interest from EU regulatory and supervisory bodies. Already from its inception, the European Banking Authority (EBA) has been attributed the mandate of *"putting in place a monitoring system to assess material environmental, social and governance-related risks, taking into account the Paris Agreement to the United Nations Framework Convention on Climate Change"*.[1] In 2020, the Authority launched a pilot exercise on a sample of 29 volunteer banks, with the goal of identifying and quantifying their exposure to climate risk and testing the stability of the financial system as a whole. Climate risk, as per the sixth report by the IPCC (2023), is defined as "*the potential for adverse consequences for human or ecological systems*" which "*can arise from potential impacts of climate change as well as human responses to climate change*". It has two main components: physical and transition risk. The first describes the direct effects of changes in the climate, which arise from chronic modifications in weather patterns, such as rising temperatures, or from acute events, such as floods and hailstorms. The second component instead includes the more indirect effects, namely those arising from regulatory risk, technological advances, and changing consumer preferences.

The results of the EBA pilot exercise on climate risk have been published in 2021, with a word of warning on the limits of the methodologies used, which should only be considered as starting points for future work on climate risk. Emphasis was also placed on the need to develop a better understanding and measurement methodology for this type of risk, and on an increase in the attention paid to the proportion of green assets and financial instruments inside bank portfolios. These include green bonds, which are debt instruments used for the funding of projects with a positive environmental impact,[2] as well as green loans, extended by banks for the financing of EU Taxonomy-aligned activities, and green mortgages, which offer favorable terms for the purchase of energy-efficient homes or properties undergoing eco-friendly upgrades. The EBA also stressed the need to better identify and quantify the transmission channels of climate risk shocks to banks' balance sheets.

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[1] Art. 29, 1. (f), Regulation (1093/2010) of the European Parliament and of the Council of 24 November 2010 establishing a European Supervisory Authority (European Banking Authority).

[2] Some examples of projects with a positive environmental impact, as per the 2021 ICMA Green Bond Principles, are: renewable energy production, transmission, appliances and products, sustainable water and wastewater management, pollution prevention and control, and energy-efficient buildings.

https://doi.org/10.1016/j.eneco.2025.108664
Received 23 May 2024; Received in revised form 31 March 2025; Accepted 4 June 2025
Available online 12 July 2025
0140-9883/

Similar conclusions were repeated in the report on the 2022 EBA climate risk stress test.

The present work aims to investigate the role of climate risk in green and non-green corporate debt instruments held and issued by banks in the three largest European Union economies by GDP: Germany, France, and Italy. The sample at hand therefore includes all the corporate green bond issuers in these three countries. Then, all of their obligations, green or not, are considered and analyzed separately, in order to highlight potential differences in their market behavior.[3] These instruments allow a focus on both the asset side of banks' balance sheets, through an study of the (green and non-green) debt issued by a number of obligors with different levels of climate exposures, and on the liability side, by also including in the analysis (green and non-green) bonds issued by the banks themselves.

The paper is structured as follows: Section 2 reviews the existing literature, highlighting the role of this work in extending it. Section 3 introduces the theoretical framework, with Section 3.1 concerning the time series analysis of corporate bond spreads, and of their relationship with physical and transition risk drivers. Section 3.2 proposes an intensity-based credit risk model for corporate bond prices including climate risk, and Section 3.3 describes the data sources of each variable under consideration. Section 4 presents the results of the analyses, with Section 4.1 relating to the framework in Section 3.1, and Section 4.2 relating to the model in Section 3.2. Finally, Section 5 concludes.

2. Literature review

Considering previous works on climate risk, Allman (2021) focuses on one indicator of physical risk, available in the United States: the Sea Level Rise (SLR) index. The risk is found to indeed be priced by the market: corporate bonds of companies with greater exposure to SLR risk bear a climate risk premium upon issuance. Furthermore, the premium is larger for geographically concentrated firms. Our work considers different physical risk indicators, with the selection being based on the previous academic literature, on the EBA Climate Stress Tests and Exercises, and on the Climate Risk Landscape reports by the United Nations Environment Programme Finance Initiative. For each variable, the granularity of the available data is also a factor in its selection, with preference given to those available at the higher frequency.

Agliardi and Agliardi (2021) propose a structural credit-risk model incorporating both uncertainty about earnings and uncertainty due to climate risks. The theoretical framework derives explicit expressions for bond prices from balance sheet values impacted by sudden climate policy shocks. They also study the interplay among the various risk drivers. Our proposed framework also leads to the adaptation of a credit risk model, in our case intensity-based, but results from the formalization of a time-series analysis on corporate bond spreads, used to identify the relevant risk factors. The choice of the intensity-based model is motivated by the frequency of the data in our study, which is well-suited for a credit risk model calibrated on daily bond prices, such as the intensity-based one, instead of balance sheet items, such as the structural one.

Bats et al. (2023) study climate risk premia in Euro area corporate bond markets. As gauges of climate risk, they use text-based indices based on news content. They find that physical risk is significantly priced in corporate bonds with longer-term maturities. It is also found in shorter-term maturities, but for the latter the premium is smaller and less significant. Our work directly uses weather variables and risk indicators, provided by European data services (such as the European Drought Observatory and the Copernicus Data Service), and translates the results into an updated credit risk model.

Transition risk has also been found to be a potential explanatory variable of financial returns, with Bolton and Kacperczyk (2019) and Po-Hsuan et al. (2023) focusing on the equity market. Both works aim to gauge whether stock prices reflect investors' demand for compensation for exposure to carbon emission risk. The variables under study are carbon dioxide emissions, in Bolton and Kacperczyk (2019), and a wider measure of toxic emissions on the part of firms, in Po-Hsuan et al. (2023). Both papers find that the stocks of companies with higher emissions earn higher returns: a carbon premium that cannot be explained by traditional risk factors. For this reason, a potential proxy of transition risk is also included in our work. This expands the analysis beyond the equity market, and evaluates the potential impact on fixed-income instruments. Therefore, we aim to contribute to the existing literature by investigating the relationship between transition risk and corporate bond spreads, and whether it is consistent with the results relating to the stock market.

3. Methodology

3.1. Time series analysis

The yield-to-maturity (YTM) of a defaultable bond incorporates the same information as the bond price, but has the advantage of being decomposable into a market risk-free or benchmark yield, y^{RF}, and a spread, s:

$$y_t = y_t^{RF} + s_t, \quad 0 \le t \le t_N,$$

where t_N is the maturity of the bond. The object of interest of the analysis are the spreads of corporate bonds, as they more purely reflect the issuer-specific component of the risk intrinsic to the instrument, and thus the issuer's exposure to the different risk factors. The spreads are not quoted on the market, so they need to be recovered from the bond YTMs by subtracting the relevant y_t^{RF} from the quoted, end-of-day y_t, $0 \le t \le t_N$. For each bond, at any time t, the relevant y_t^{RF} is the YTM of a bond with the same principal, coupon schedule, coupon periodicity, and maturity, but with the credit risk associated with the entity behind the benchmark rate. We take as y^{RF} the risk-free yield associated with the rates bootstrapped from the EURIBOR Interest Rate Swap (IRS) curve.

Benchmark bonds with features identical to the bonds in this analysis are not generally available, they need to be constructed synthetically. At every time t, the bond price $P_{RF}(t, t_N)$ of a bond with the same characteristics as the defaultable bond is recovered. The discount rate for the cash flows, $r^{RF}(t, t_i), i = 1, \ldots, N$, is the spot rate corresponding to the benchmark at time t, with tenor equal to t_i, the time to each cash flow, i.e.

$$P_{RF}(t, t_N) = \sum_{i=1}^{N} \frac{cF}{(1 + r^{RF}(t, t_i))^{t_i - t}} + \frac{F}{(1 + r^{RF}(t, t_N))^{t_N - t}}, \tag{1}$$

where the spot rate $r^{RF}(t, t_i)$ is the YTM, at time t, on a risk-free zero-coupon bond with maturity t_i.

The benchmark spot rates are not immediately available, they are thus bootstrapped from the term structure of EURIBOR IRS rates $r^{IRS}(t, t_N)$, which is quoted at each t for a set of maturities. The times to each bond cash flow are different for each bond and change every day with t, meaning that an interpolation scheme for the benchmark spot rates is required. We land on a choice widely used in the literature, the Nelson–Siegel–Svensson model proposed in Nelson and Siegel (1987) and extended in Svensson (1994). The Nelson–Siegel–Svensson model describes the term structure of spot continuously compounded rates by the following expansion:

$$r(\tau) = b_0 F_0(\tau) + b_1 F_1(\tau) + b_2 F_2(\tau) + b_3 F_3(\tau),$$

[3] For the purpose of this work, we will consider as green bonds those adhering to the 2021 ICMA Green Bond Principles, as described in https://www.icmagroup.org/assets/documents/sustainable-finance/2021-updates/green-bond-principles-june-2021-100621.pdf. The non-green bonds are all remaining bonds by those same issuers, which have not been explicitly labeled as green.

where b_0, b_1, b_2, b_3 are the coefficients of expansion, $\tau = t_i - t$ is the tenor of each rate, and the basis functions are given by:

$$F_0(\tau) = 1$$
$$F_1(\tau) = \frac{1-\exp(-\tau/\zeta)}{\tau/\zeta}$$
$$F_2(\tau) = \frac{1-\exp(-\tau/\zeta)}{\tau/\zeta} - \exp(-\tau/\zeta)$$
$$F_3(\tau) = \frac{1-\exp(-\tau/\kappa)}{\tau/\kappa} - \exp(-\tau/\kappa).$$

The basis functions represent the traditional components of a term structure: $F_0(\tau)$ represents the long-term level, $F_1(\tau)$ represents an exponential decay, where the term structure can have an upward slope (when $b_1 < 0$) or a downward one (when $b_1 > 0$). Finally, $F_2(\tau)$ and $F_3(\tau)$ replicate changes in the overall curvature of the yield curve. The parameters ζ and κ determine the location of the humps or the troughs, as well as their steepness.

Once $P_{RF}(t, t_N)$ is obtained, y_t^{RF} is found as:

$$\arg\min_{y_t^{RF}} \left(P_{RF}(t, t_N) - \sum_{i=1}^{N} \frac{cF}{(1+y_t^{RF})^{t_i - t}} - \frac{F}{(1+y_t^{RF})^{t_N - t}} \right)^2.$$

The procedure is repeated for each t, $0 \le t \le t_N$, and for each bond.

We detect non-stationarity and autocorrelation in the time series of the spreads. Appropriate models to account for such features are those of the ARIMA(p,d,q) class. Additionally, the residuals are not normally distributed, display heavy tails and heteroskedasticity. We thus fit ARIMA(p,d,q) models with conditionally Student-t-distributed innovations having GARCH variance to each bth time series of spreads, $\{s_{b,t}\}_{t\in\mathbb{N}}$

$$\left(1 - \sum_{j=1}^{p} \varphi_{b,j} L^j\right)(1-L)^d s_{b,t} = \theta_{b,0} + \left(1 + \sum_{j=1}^{q} \theta_{b,j} L^j\right)\epsilon_{b,t}, \quad t \in \mathbb{N},$$

$$\epsilon_{b,t} | \mathcal{F}_{t-1} \sim t_{v_b}(0, \sigma_{b,t}),$$

$$\sigma_{b,t} = \sqrt{\frac{v_b - 2}{v_b} h_{b,t}},$$

$$h_{b,t} = \omega_b + \sum_{p=1}^{P_b} \psi_{b,p}\epsilon_{b,t}^2 + \sum_{q=1}^{Q_b} \phi_{b,q} h_{b,t-q},$$

where L is the lag operator, $\theta_{b,0}$ is a constant, $\epsilon_{b,t}$ is the model residual at time t of the bth time series, $h_{b,t}$ is its conditional variance, $\sigma_{b,t}$ is the shape parameter of the corresponding Student t distribution, and v_b are its degrees of freedom. We extend the model to include $X_{b,j}, j = 1, \dots, n$ exogenous regressors, lagged of one period, in order to evaluate their potential significance. The resulting model is of the ARIMAX type

$$\left(1 - \sum_{j=1}^{p} \varphi_{b,j} L^j\right)(1-L)^d s_{b,t} = \theta_{b,0} + \left(1 + \sum_{j=1}^{q} \theta_{b,j} L^j\right)\epsilon_{b,t} + \sum_{j=1}^{n} \alpha_{b,j} X_{b,j,t-1}.$$

The exogenous regressors include traditional determinants, selected on the basis of extant literature, such as Longstaff and Schwartz (1995), Collin-Dufresne et al. (2001), and Chen et al. (2007), alongside proxies of climate risk.

Multiple traditional determinants are selected. Firstly, we include bond liquidity, which is found to be priced in corporate yield spreads in Chen et al. (2007), and proxy it by closing percent quoted bid–ask spread. Firm leverage, defined as the book value of debts divided by total book value of assets, is also added, because of the link between a firm's capital structure and its default probability, given that default events are triggered when the leverage ratio approaches one. Return on Equity, representing firm profitability and health, is also considered, due to its ties with the probability of default, as found in Arbel et al. (1977). Following Collin-Dufresne et al. (2001), changes in business climate are also accounted for, through the log-returns of each country's main stock market index, while the VIX index is used as a proxy of implied option volatility. In fact, in line with the contingent-claims approach to corporate liabilities derived from Merton (1974), a debt claim is analogous to a short position in a put option. Since option value increases with volatility, credit spreads are also expected to be affected by it. Log-returns of Eurozone corporate bond indices with rating matching each bond are also included, together with local government yields, yield curve convexity and yield curve slope, as in Collin-Dufresne et al. (2001). An important link exists between prevailing interest rates and corporate bonds, with Longstaff and Schwartz (1995) finding that the correlation between default risk and interest rates has a significant effect on the properties of bond spreads.

As for the local government yield, it is necessary to select a tenor. Multiple options 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 options are fit, one at a time, and the last one is chosen, as it displays the highest explanatory power. Hence, for every day in the sample window, the duration of each bond is computed and the government yield with the corresponding maturity is interpolated from the yield curve of that date, and used as a regressor. 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 government 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 government 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 b_1 and b_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. The NSS parameters b_1 and b_2 resulting from fitting the model to the daily continuously-compounded equivalents of the benchmark rates are selected in the final version of the ARIMAX model, as they are found to have the greater explanatory power.

Multiple variables and potential proxies for climate risk are considered, with the selection being based on the previous academic literature, on the EBA Climate Stress Tests and Exercises, and on the Climate Risk Landscape reports by the United Nations Environment Programme Finance Initiative. For each variable, the granularity of the available data is also a factor in its selection, with preference given to the ones available at the higher frequency.

Transition risk, as in Livieri et al. (2023), is proxied by 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.

As for physical climate risk, the current approach to Climate Stress Testing by the European Union restricts physical risk scenarios to instantaneous shocks, thus exclusively focusing on acute risks and on the ability of the financial system to withstand them. On the other hand, the scope of this analysis is broader and also includes the link of the bond market with continuous climate variables, some of which are taken as proxies of chronic physical risk. In line with the 2022 Climate Stress Test by the European Central Bank (2022), drought and flood risks are accounted for. The Soil Moisture Index Anomaly (SMA) is selected, which represents the deviation from the usual water availability in the same time of the year. Values below the wilting point (when the soil is severely dry) are taken as a proxy for drought anomalies, and those above the field capacity (when the soil is unable to absorb any more water) as representative of flood risk. The Combined Drought Indicator (CDI) was also considered, but it was found to have a lower explanatory power than the SMA, and was thus excluded.

The non-seasonal component of average daily wind speed is also included, for both the Zonal (eastward) and the Meridional (northward) wind components, with a vertical coordinate in height of 10 m. Its role is tied to the production of renewable energy and, in its extreme values, to storms, hurricanes and typhoons (as per the 2023 Climate Risk Landscape report by the United Nations Environment Programme Finance Initiative, Carlin et al., 2023).

The non-seasonal component of average daily temperature is also considered in the analysis, as an indicator of chronic physical risk, for its impact on worker productivity and energy demand.

Finally, in line with the physical risk drivers identified in Carlin et al. (2023), an indicator of wildfire risk is included: the Copernicus Fire Weather Index (FWI). It is available at the daily frequency and accounts for the effects of fuel moisture (linked to humidity and 24-h accumulated precipitation) and wind. The higher its value, the more favorable the meteorological conditions to trigger a wildfire.

All variables are checked for stationarity, and their one-period increments are considered, whenever necessary. Additionally, the regressors and the regressands are standardized, in order to facilitate the comparability of the coefficients. Lastly, a test of multicollinearity between regressors, based on variance inflation factors, is carried out before fitting the models, to ensure the reliability of the estimates.

3.2. An intensity-based climate risk model

To further study the dependence between the default probabilities implied by risky bonds, on the one hand, and climate variables, on the other, we exploit the methodology based on stochastic hazard rates proposed by Duffie and Singleton (1999). As shown in Driessen (2005), this approach performs well when dealing with bond pricing that includes external factors, which corresponds to our setting. We thus propose an extension of it, to include physical risk factors.

The strength of the methodology relies on the fact that it does not require any assumption about the nature of the firm's liabilities, as opposed to the structural model of Merton (1974). The approach in Duffie and Singleton (1999) is based on the modeling of the stochastic hazard rate that drives the survival probability of a firm, and the only assumption required is that it must be a positive process. Then, given a probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$, and letting γ_t be an $\mathcal{F}_t$-adapted process and τ the time of default, the survival probability of a given firm, until a certain time $T \geq 0$, is described by

$$P(\tau > T|\mathcal{F}_\infty) = e^{-\int_0^T \gamma_u du}, \tag{2}$$

where γ_t, $t \geq 0$, is the hazard rate. This formulation allows us to express the price of a risky zero coupon bond $P_R(0,T)$, with maturity T, as

$$\begin{aligned} &P_R(0,T) \\ &= P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}[P(\tau > T|\mathcal{F}_\infty)|\mathcal{F}_0] + \delta P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}[P(\tau \leq T|\mathcal{F}_\infty)|\mathcal{F}_0] \\ &= P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}[P(\tau > T|\mathcal{F}_\infty)|\mathcal{F}_0] + \delta P_{RF}(0,T)(1-\mathbb{E}^{\mathbb{Q}}[P(\tau > T|\mathcal{F}_\infty)|\mathcal{F}_0]) \\ &= P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right] + \delta P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}\left[1-e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right], \end{aligned} \tag{3}$$

where δ is the recovery rate, which we assume to be a constant, $P_{RF}(0,T)$ is the risk-free discount factor with maturity T, and $\mathbb{Q}$ is the risk-neutral measure equivalent to the physical risk measure $\mathbb{P}$. The change of measure is defined by the Radon–Nikodym derivative

$$\frac{d\mathbb{Q}}{d\mathbb{P}}\Big|_T = \exp\left\{-\int_0^T \pi_u dB_{0,u} - \frac{1}{2}\int_0^T \pi_u^2 du\right\}, \tag{4}$$

where π_t is the market risk premium and $B_{0,t}$ is the Brownian Motion driving the firm-specific factor of the hazard rate process.

The stochastic hazard rate γ_t is a linear combination of the firm-specific factor, $\gamma_{0,t}$, modeled with Cox–Ingersoll–Ross (C.I.R) process (Duffie and Singleton, 1999 and Driessen, 2005) and which incorporates everything that is not explicitly modeled, and the physical risk proxies included in our study. These are the Fire Weather Index $\gamma_{1,t}$, the de-seasonalized average daily Eastward wind speed, $\gamma_{2,t}$, the de-seasonalized average daily Northward wind speed, $\gamma_{3,t}$, the flood index, $\gamma_{4,t}$, the drought index, $\gamma_{5,t}$, and the positive de-seasonalized average daily temperature, $\gamma_{6,t}$[4]:

$$\gamma_t = \gamma_{0,t} + \beta_1\gamma_{1,t} + \beta_2\gamma_{2,t} + \beta_3\gamma_{3,t} + \beta_4\gamma_{4,t} + \beta_5\gamma_{5,t} + \beta_6\gamma_{6,t}, \tag{5}$$

where the parameters $\beta_i \in \mathbb{R}^+$, $i = 1,\ldots,6$, measure the impact of the ith factor on the survival probability.

The Fire Weather Index, the de-seasonalized average daily Eastward and Northward wind speed, and the positive part of the de-seasonalized average daily temperature are modeled as Ornstein–Uhlenbeck processes driven by pure jump Lévy processes, as in Benth et al. (2018) and Benth et al. (2021). The flood and drought indices, on the other hand, are modeled as C.I.R. processes. The choice of this type of process is due to the non-normality of the corresponding time series, while the reason for using pure jump Lévy processes for the fire and wind indices is the need to allow for a non-zero probability of the event when they have a value or an increment of zero. As for the temperature, we consider the positive part of the de-seasonalized average daily temperature – representing excessive heat – as the credit risk model requires risk-factor processes to be positive (henceforth referred to as "excess temperature"). The resulting time series is mean-reverting, with increments of size zero, and can therefore be successfully modeled with an Ornstein–Uhlenbeck processes driven by a pure jump Lévy process.

Therefore, the dynamics of the Fire Weather Index and the de-seasonalized average daily Eastward, Northward wind speed, and excess temperature are

$$\begin{aligned} d\gamma_{i,t} &= -k_i\gamma_{i,t}dt + dL^{\mathbb{Q}}_{i,t}, \\ \gamma_{i,t} &= \gamma_{i,t_0}e^{-k_i(t-t_0)} + \int_{t_0}^t e^{-k_i(t-u)}dL^{\mathbb{Q}}_{i,u}, \end{aligned} \tag{6}$$

where $L^{\mathbb{Q}}_{i,t}$, with $i = 1,2,3,6$, are independent compound Poisson processes with intensity λ_i and exponential jump size of expected value η_i. The dynamics of the firm-specific factor, flood, and drought indices are represented by

$$d\gamma_{i,t} = k_i(\theta_i - \gamma_{i,t})dt + \sigma_i\sqrt{\gamma_{i,t}}dB^{\mathbb{Q}}_{i,t}, \tag{7}$$

where $B^{\mathbb{Q}}_{i,t}$, with $i = 0,4,5$, are independent Brownian Motions. We assume that the physical risk variables have the same dynamics under $\mathbb{P}$ and $\mathbb{Q}$, i.e. $L^{\mathbb{Q}}_{i,t} = L^{\mathbb{P}}_{i,t}$, $i = 1,2,3,6$, and $B^{\mathbb{Q}}_{i,t} = B^{\mathbb{P}}_{i,t}$, $i = 4,5$.

For C.I.R. processes, the explicit solution of

$$\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_{t_0}^t \gamma_u du}\middle|\mathcal{F}_0\right],$$

which appears inside Eq. (3), is given by

$$\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^t \gamma_{i,u} du}\middle|\mathcal{F}_0\right] = \exp\{A_i(0,t) - C_i(0,t)\gamma_{i,t}\}, \tag{8}$$

where,

$$\begin{aligned} C_i(0,t) &= \frac{2(\exp\{td_i\}-1)}{2d_i + (k_i+d_i)(\exp\{td_i\}-1)}, \\ A_i(0,t) &= \frac{2k_i\theta_i}{\sigma_i^2}\log\left\{\frac{2d_i\exp\{(k_i+d_i)t/2\}}{2d_i + (k_i+d_i)(\exp\{td_i\}-1)}\right\}, \\ d_i &= \sqrt{k_i^2 + 2\sigma_i^2}. \end{aligned} \tag{9}$$

On the other hand, for the pure-jump Lévy-driven Ornstein–Uhlenbeck process, the solution is given by

$$\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^t \gamma_{i,u} du}\middle|\mathcal{F}_0\right] = \exp\{H_i(0,t) + M_i(0,t)\gamma_{i,t}\}, \tag{10}$$

where,

$$\begin{aligned} M_i(0,t) &= \frac{1}{k_i}\left(1-e^{-k_i t}\right), \\ H_i(0,t) &= \int_0^t \lambda_i\left(\frac{\eta_i}{\eta_i + \frac{1}{k_i}(1-e^{-k_i(t-s)})} - 1\right)ds. \end{aligned} \tag{11}$$

[4] The temperature risk factor ($\gamma_{6,t}$) is not needed for the German and Italian issuers, as it is never significant, but is necessary for some of the French firms.

The solutions for the C.I.R. dynamic and for the Lévy OU process, in Eq. (8) and (10) respectively, are then used in conjunction with Eq. (5) inside Eq. (3), to recover explicit formulas for model-implied zero coupon bond prices. Conditional independence is then assumed between each hazard rate component and the risk-free short rate. The resulting pricing equation for the risky zero coupon bond is[5]:

$$P_R(0,T) = P_{RF}(0,T) \prod_{i=0,4,5} e^{A_i(0,T)-C_i(0,T)\gamma_{i,0}} \prod_{i=1,2,3,6} e^{H_i(0,T)-M_i(0,T)\gamma_{i,0}} + \delta P_{RF}\left(1 - \prod_{i=0,4,5} e^{A_i(0,T)-C_i(0,T)\gamma_{i,0}} \prod_{i=1,2,3,6} e^{H_i(0,T)-M_i(0,T)\gamma_{i,0}}\right), \tag{12}$$

where A_i, C_i, H_i and M_i are defined in Eq. (9) and (11). More details on the derivation of Eq. (12) are available in Appendix A.

Finally, we seek to rank the impact of the different risk factors on the hazard rate of each issuer. Each climate variable has a different scale, so a simple comparison of the β_i coefficients is not sufficient. The mean reverting structure of the dynamics allows us to define the expected long-level impact of each variable for a given issuer as $\lim_{T\to+\infty} \beta_i \mathbb{E}^{\mathbb{Q}}[\gamma_T]$. For the C.I.R. process, this limit equates to $\beta_i\theta_i$, while for the OU Lévy processes it is $\beta_i\lambda_i/(\eta_i k_i)$. These quantities represent the expected long-range level of the climate variable on the hazard rate and can be used as a way to rank the climate resilience of a corporation with respect to each variable. More details on the derivation of these quantities are available in Appendix A.1.

3.3. The data

Our initial sample is comprised of corporate bonds from Eurozone firms which have issued at least one green bond. Due to the information intensity of some of the required regressors (variables such as leverage and Return On Equity require the manual collection of data from balance sheets over an almost 10 year period) we have restricted the analysis to German, French, and Italian issuers, which are the largest Eurozone (and EU) economies by GDP. The sample includes 43 German, 42 French, and 19 Italian firms, which are all the corporate green-bond issuers of the respective countries in the time frame under consideration, which goes from 01/01/2014 to 27/03/2023. In order to facilitate estimator convergence, we restrict our sample to bonds with at least 100 observations. In order to remove the impact of exchange rate risk, which is not of interest for this study, we only consider euro-denominated bonds.

Data on bond bid, ask, and mid prices, bond YTMs, IRS rates, government yield curves, the VIX index, Eurozone corporate bond indices, national stock market indices, and EU carbon allowance prices is taken from Refinitiv Datastream. Balance sheet data is taken from the AIDA database, for some Italian firms. For others, and for the German and French issuers, it is retrieved from the publicly available individual balance sheets of each firm.

As for physical risk variables, the SMA is provided by the Copernicus European Drought Observatory, while the FWI, the wind speed, and the temperature indicators are taken from the Copernicus *ERA5 hourly data on single levels from 1940 to present* database. They are averaged daily and on the latitude and longitude coordinates, converted to the EPSG:4326 Geodetic coordinate system, falling within the boundaries of each country.

[5] The result is obtained under the assumption of conditional independence between each hazard rate component and the short rate, and under the assumption that the payment in case of default will happen at bond maturity.

4. Results

The results of the first portion of the analysis, presented in Section 4.1, enable us to identify which of the climate risk variables are significantly related to changes in corporate bond spreads, and for which bond issuers. The second portion of the analysis, reported in Section 4.2, uses this information to fit the appropriate credit risk model to each issuer.

4.1. Time series results

The results of the analysis are collected in Tables B.9–B.52, divided by issuer. They display, for each firm, the number (denoted by "Nr. (S)") of statistically significant relationships between its green and non-green bonds, on the one hand, and the physical risk proxies (Eastward wind, Northward wind, Drought, Flood, and FWI), on the other. The tables also show the average coefficient $\alpha_{b,j}$ of the significant bonds ("Avg. Coefficient").

In order to enhance the legibility of the work, not all sample issuer tables are reported. We only focus on those which are either significantly exposed to at least one climate risk variable, or which have only issued green bonds and hence do not allow a direct comparison with their non-green instruments. We define the exposure as significant if at least half of the issuer's bonds have a statistically significant relationship with at least one climate risk proxy, meaning that the null hypothesis of a zero-sized coefficient was rejected at most at the 5% significance level. From herereon, we will refer to this final subset of firms as the "relevant issuers". Additional consideration is given to the difference in the liquidity of the significant ("Avg. Liquidity (S)") and the non-significant ("Avg. Liquidity (NS)") bonds of the relevant issuers (proxied by the average percentage quoted bid–ask spread), to their average age ("Avg. Age (S)" and "Avg. Age (NS)"), in years, and to differences in their residual maturities ("Avg. Res. Maturity (S)" and "Avg. Res. Maturity (NS)"), also in years. These factors affect the sensitivity of bond prices, so they are reported as potential explanations for the different degree of reactivity to physical risk proxies of 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. Therefore, in some cases, such as Tables B.12, B.19, B.33, B.36, B.39, and B.40, we include the issuer among the relevant issuers even if fewer than half of its outstanding bonds (denoted by "Total Nr".) are significantly related to the climate risk proxies at the 5% level, as long as the significant bonds are also those with the lower age, the greater liquidity (represented by a smaller bid–ask spread), and/or the greater residual maturity.

As for the transition risk proxy, i.e. the log-returns of EU carbon allowances, no issuer satisfied these criteria. The significant relationships were sparse, among issuers, and discordant, in line with the findings in Livieri et al. (2023). For this reason, the credit risk model introduced in Section 3.2 and calibrated in Section 4.2 only incorporates physical risk drivers.

The different situations that we encounter can be grouped into three main settings. The first setting, as in the cases reported in Tables B.12, B.14, B.30, B.31, B.33, B.34, B.36, B.39, and B.40, represents issuers which are significantly related to some physical risk variables, but those variables have a negative or a null relationship with green bonds (meaning that the bond spreads tend to decrease or not react, when the size of the physical risk variable increases), and a positive one with non-green bonds of the same issuer (meaning that the bond spreads tend to increase, when the size of the physical risk variable increases). In these cases, the market seems to treat green bonds as hedging against physical risk: although they have the same issuer as the non-green ones, their prices (and thus spreads) react as if they were unaffected or positively affected by increases in the physical risk proxies. As it appears, the nature of the green bonds of these issuers, with their funds being committed to projects with a positive environmental impact, makes them more desirable by the market than their non-green counterparts - and therefore less reactive to climate risk. Interestingly, the most represented sector in this second setting is that of banks. In their case, green bond issuance is usually tied to the funding of green loans, which are extended to borrowers aiming to finance sustainable projects. The different treatment on the part of the market could indirectly reflect a lower perception of risk tied to this type of credit.

The second setting, as in the cases in Tables B.9, B.10, B.13, B.17, B.19, B.32, B.38, and B.41 shows situations in which both green and non-green bonds have a comparable relationship with the climate risk proxy of interest, in terms of sign of the coefficient and of number of significant relationships. For these firms, the market treats green bonds as equivalent, in terms of physical risk exposure, to non-green ones. Interestingly, this setting includes B.13 and B.17, which belong to the traditional energy sector. As is instead shown in the next paragraph, the renewable energy producers in the sample all are either unaffected by climate risk, or treated by the market as offering a hedge against them. This could point to the view, on the part of the market, that the two traditional energy companies are not sufficiently green for their green bonds to be treated as hedges against climate risk, while the opposite is true for the renewable energy producers.

The third setting is that of companies which have only issued green bonds. They are mostly producers of renewable energy and real estate banks, and the statistically significant negative relationship between their spreads and some climate risk proxies can offer an hedge against them, as in the cases in Tables B.11, B.15, B.16, B.18, B.20, B.42, B.43, B.45, B.48, B.49, and B.52. However, some of the issuers of exclusively green bonds have a positive (and thus risky) relationship with a different climate variable, such as B.35 and B.37. Finally, we include the cases in Tables B.21, B.22, B.23, B.24, B.25, B.26, B.27, B.28, B.29, B.44, B.47, B.50, and B.51, which have no significant relationship with any climate risk variable. Among them are multiple providers of environmental services, leaders in low-carbon transportation, and companies involved in the acquisition and management of real estate.

4.2. Fitting and evaluating the intensity-based model

The initial step of the procedure requires fitting the stochastic process to the physical risk climate variables of the two countries, Italy (“IT”) and Germany (“DE”). The variables are standardized between zero and 1, to facilitate comparability and fit. The estimation for the C.I.R. and Lévy-driven Ornstein–Uhlenbeck processes is carried out via indirect inference, as in Gourieroux et al. (1993). The auxiliary process, for all the cases, is an AR(1), while the structural process is either the C.I.R. or the Lévy Ornstein–Uhlenbeck, depending on the variable at hand. The continuous time process in the indirect inference algorithm has been simulated via Euler discretization of the SDE governing the corresponding process. In the case of the C.I.R., the Matlab built-in function is used.

The results of the fits are in Table 1, for the Ornstein–Uhlenbeck Lévy-driven processes, and in Table 2 for the C.I.R. processes. Figs. 1(a) and 1(b) show the average daily eastward and northward wind speed over the sample period, respectively. The averages are taken on the absolute values (disregarding information about the wind direction, represented by the sign) and mapped by latitude and longitude for the three countries under study, France, Germany, and Italy. Germany and France report the overall highest average speed for both the eastward and northward components of wind. The calibrated parameters in Table 1 offer greater detail on this overall fact: for France and Italy, the frequency of Lévy jumps (λ_i) of the eastward component of wind is superior to that of the northward component. Yet, for Italy, the expected jump size (η_i) is slightly larger for the northward wind. In the German case, both λ_i and η_i are larger for the eastward component of wind. In Fig. 1(d) we then report the average value of the daily temperature

Table 1
Calibrated parameters of the Lévy-driven Ornstein–Uhlenbeck processes for weather variables.

	k_i	λ_i	η_i
IT Eastw. Wind	0.63806	1.37484	0.08659
IT Northw. Wind	0.60216	1.21135	0.09293
IT Excess Temp.	0.37022	0.22088	0.19722
IT FWI	0.01799	0.01467	0.22804
DE Eastw. Wind	0.48593	1.25013	0.10196
DE Northw. Wind	0.65904	1.66522	0.08456
DE Excess Temp.	0.35372	0.20294	0.21450
DE FWI	0.12069	0.06761	0.08168
FR Eastw. Wind	0.50448	1.16548	0.10046
FR Northw. Wind	0.60894	1.39475	0.09106
FR Excess Temp.	0.33334	0.18637	0.19940
FR FWI	0.07080	0.04022	0.13719

Table 2
Calibrated parameters of the C.I.R. processes for weather variables.

	k_i	θ_i	σ_i
IT Drought	0.0017	0.3256	0.0399
IT Flood	0.0017	0.3623	0.0542
DE Drought	0.0004	0.9938	0.0145
DE Flood	0.0005	0.8482	0.0335
FR Drought	0.0005	1.0298	0.0153
FR Flood	0.0003	1.0409	0.0096

which, as expected, is highest at lower latitudes. Germany displays a greater level of uniformity and lower average temperatures, while Italy and France have a greater geographical variability, with overall higher average values. Fig. 1(c) shows the average FWI index and highlights greatest level of risk in Italy. In terms of process parameters, the frequency of Lévy jumps in the sample period is actually highest in Germany, but average jump size is substantially higher in Italy. Finally, the speed of mean reversion (k_i) is highest in the German case, indicating a greater level of uniformity.

Consistently with the time-series analysis, the values of the drought index correspond to the absolute value of the observations below the wilting point in the SMA index. This is done for ease of interpretation, so that greater values of the index (which would otherwise be negative) correspond to greater levels of risk. Additionally, for what concerns the maps of daily averages in Figs. 2(a) and 2(b), the extreme observations have been capped at 1, in order to display the large variety of values at the lower end of the scale. In Table 2 it can be seen that the C.I.R. processes of the three countries have similar speed of mean reversion, with Italy having the highest. As for the estimated long-term mean (θ_i), those of the French and German processes are consistently higher, while the Italian ones have the greatest variability overtime (represented by σ_i).

The second step of the procedure requires fitting the appropriate intensity-based models to daily bond prices, in light of the results in Section 4.1. Given that the model is constructed to incorporate those factors that increase the riskiness of the firm, as it assumes a positive process for the hazard rate, for each issuer we only include the climate variables that display a positive (and statistically significant) coefficient in Section 4.1. This results in a smaller subset of the relevant issuers, but the choice is made to enhance the reliability of the results. A looser approach would “force” the optimization function of the credit risk model to calibrate parameters for risk factors with limited to no significance for the other issuers, leading to unreliable conclusions about their size and impact.

The calibration is performed via least squares, minimizing the sum of daily squared distances between the prices implied by the model in Section 3.2, denoted by $P_R^{Model}(t, t_N)$, and the observed mid quotes of daily closing market prices, denoted by $P_R^{Market}(t, t_N)$.

$$\underset{\beta,k_0,\theta_0,\sigma_0,\gamma_{0,t_0}}{\arg\min} \sum_{t=1}^{T} \Big(P_R^{Market}(t, t_N) - P_R^{Model}(t, t_N) \Big)^2, \tag{13}$$

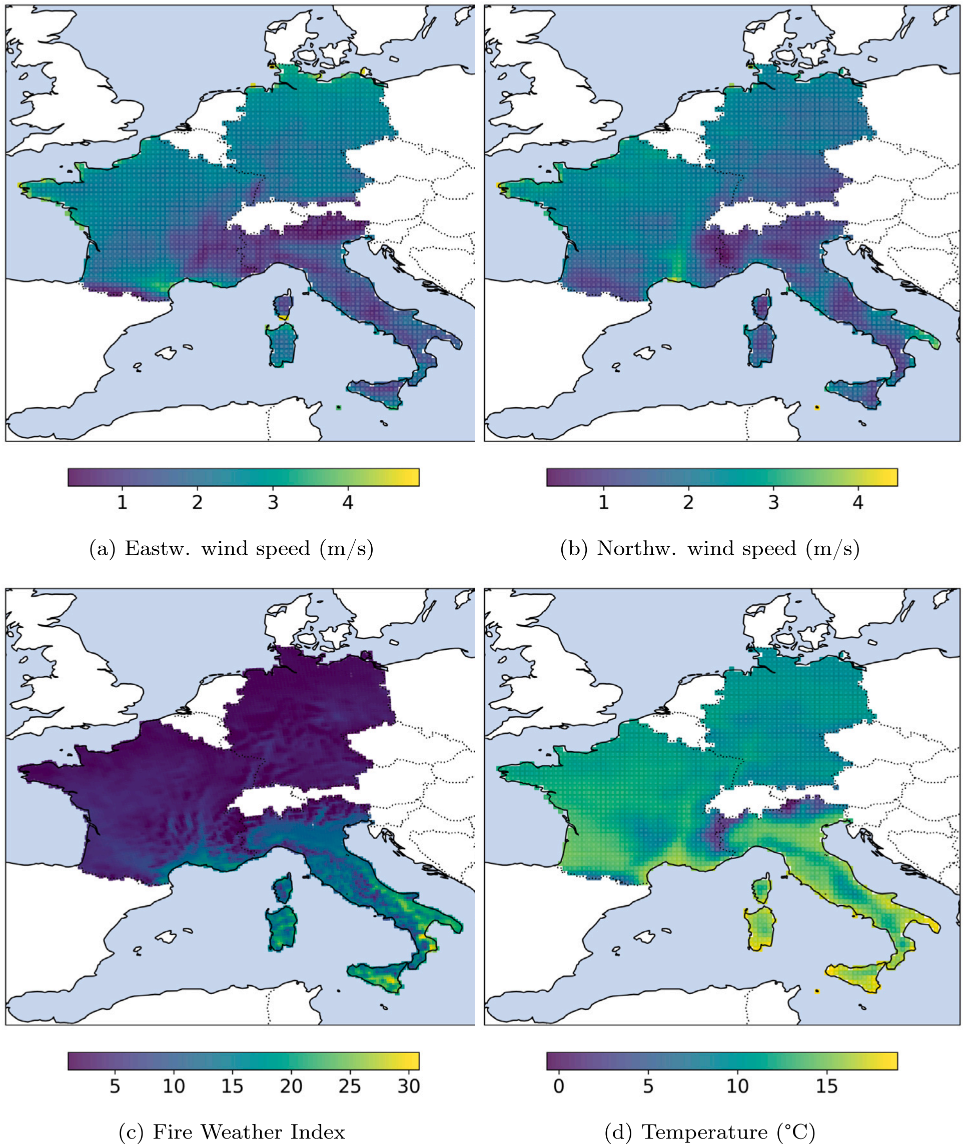

Fig. 1. Average daily values of wind, fire weather, and temperature indices over the sample period.

where T is the last day in our observation window, and t_N is the maturity of each bond. In doing so, we recover the daily parameters $k_0, \theta_0, \sigma_0, \gamma_{0,t_0}$ driving the firm-specific component of the hazard rate, $\gamma_{0,t}$, as well as the subset β of the parameters β_i, $i = 1, \dots, 6$, which represent the impact of the relevant physical risk factors on each issuer's hazard rate. For issuers belonging to the first setting of Section 4.1, where green bonds were not negatively affected by physical risk drivers, we only fit the model on the time series of prices of non-green bonds. For firms belonging to the second setting, in which both green and non-green bonds have a comparable relationship with the climate risk proxy of interest, we fit the model on the time series of prices of both types of bonds. Lastly, for issuers belonging to the third setting, we calibrate the model only on green bonds, and only if they have a risky relationship with at least one climate variable.

The results are shown in Tables 3, 4, and 5 for Italy, Germany, and France, respectively. For this final set of issuers in the Germany and Italy, the deseasonalized daily mean temperature was not a risk factor of interest. It was thus excluded from the fit of the models. Interestingly, all relevant Italian issuers were exposed to the flood risk indicator, with the airport being the most negatively affected. This seems reasonable, considering the dependence of the index with rainfall and negative weather conditions.

As for German issuers, the resulting risk factors were divided by industry: the most frequent was the deseasonalized average daily wind speed, which exclusively affected all renewable energy producers in the relevant sample. On the other hand, all of the banks were exposed to either drought or flood risk.

In the French case, as in Germany, all of the banks in the sample were exposed to either drought or flood risk. Additionally however, in contrast to the German and Italian cases, temperature proved to be a risk factor of interest. It was the second most relevant climate variable of all, with drought being the first.

The relative dimension of the different beta coefficients allows for a comparison between the contribution of the different risk factors to the hazard rate of the issuer, and thus to its default probability. However, the size of the beta is not the only element to consider: the

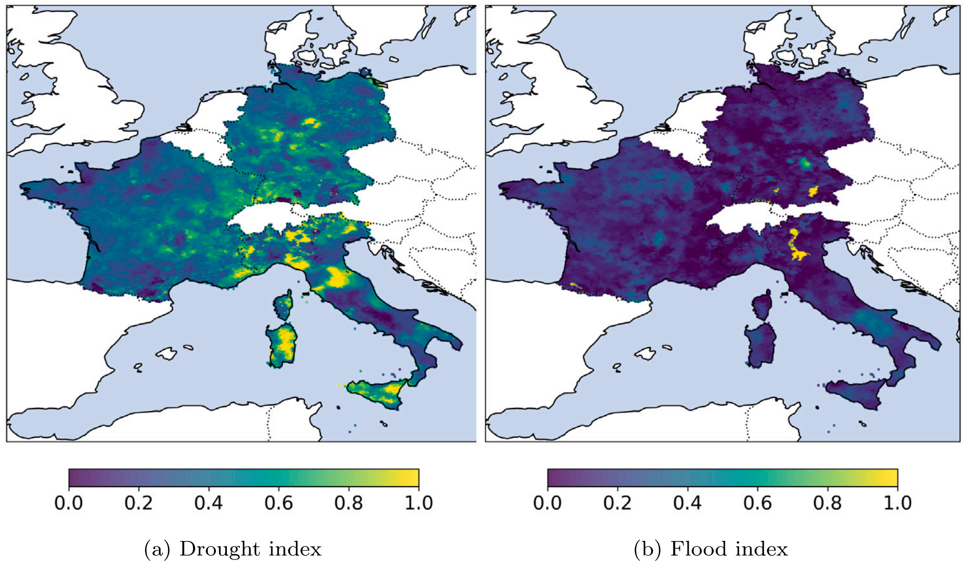

Fig. 2. Average daily values of drought and flood indices over the sample period.

Table 3
Calibrated parameters of relevant Italian issuers.

	AEROPORTI DI ROMA SPA	ALPERIA SPA	ASSICURAZIONI GENERALI SPA	BANCO BPM SPA
k_0	4.36413	0.77504	2.00981	7.27899
θ_0	0.23149	0.13273	0.81920	0.03213
σ_0	0.28353	1.57245	0.05291	8.20626
γ_{0,t_0}	1.80475	0.17044	0.00891	0.06405
$\beta_{Drought}$	–	–	–	0.35635
β_{Flood}	4.80387	0.00216	0.13268	0.37458
β_{FWI}	0.73911	–	–	–
$\beta_{Northw.Wind}$	0.01201	–	–	–

Table 4
Calibrated parameters of relevant German issuers.

	COMMERZ BANK AG	EUROGRID GMBH	EUSOLAG EUROPEAN SOLAR AG	LANDES BANK BADEN WUERT-TEMBERG	MUENCHE NER HYPOTHEKEN-BANK EG	RWE AG
k_0	1.38567	2.74877	4.75668	0.79609	0.29676	0.02648
θ_0	0.90574	0.38562	0.13413	0.00034	0.09205	3.11306
σ_0	1.24954	1.54518	0.09267	0.04185	0.02055	3.16466
γ_{0,t_0}	0.07029	0.82744	0.00162	0.00633	0.00000	0.44693
$\beta_{Eastw.Wind}$	–	0.00071	–	–	–	0.00154
$\beta_{Drought}$	–	–	–	0.01054	0.04972	–
β_{Flood}	2.34402	–	–	–	–	–
β_{FWI}	–	–	–	–	–	–
$\beta_{Northw.Wind}$	–	–	0.00731	–	–	–

total impact of the factor will also depend on the parameters of its process and, in general, on its expected value. Tables 6–8 display the long-term impact estimates of each climate variable, computed with the procedure described in Section 3.2.

4.3. Robustness check

We finally perform a robustness check of the climate risk extension of the intensity-based model, from hereon referred to as the "proposed model". On the same data, for each issuer, we fit another model, henceforth referred to as the "alternative model", which excludes all weather variables and only includes the firm-specific component of the hazard rate in Eq. (5), i.e. $\gamma_{0,t}$. According to the theory, this component incorporates all other non-explicitly specified risk drivers that affect a company's probability of default. If those risk drivers indeed include the climate variables that we make explicit in our analysis, as we postulate based on the results in Section 4.1, we expect the quality of the fit of the proposed model to be comparable, if not superior, to the quality of the fit of the alternative model.

We test this hypothesis by comparing the means μ_P and μ_A of the objective functions, as defined in Eq. (13), minimized daily by the proposed model and by the alternative model, respectively. This is done through the one-tailed Welch's t-test for comparing means with unequal variances. The null hypothesis is $H_0 : \mu_P <= \mu_A$, while the alternative hypothesis is $H_1 : \mu_P > \mu_A$, meaning that the proposed model performs worse and has, on average, a higher objective function than the alternative one. The resulting statistics are reported in Table B.53, disaggregated over multiple months. Welch's t-test mostly fails to reject the null hypothesis at the 5% and 1% significance levels, but the quality of the fit changes across the months, suggesting a time-changing nature in the link with the risk factors. For some issuers, the opposite alternative hypothesis $H_1 : \mu_P < \mu_A$, representing the superiority of the proposed model, is accepted at the 5% or 1% significance levels.

Table 5
Calibrated parameters of relevant French issuers.

	BPCE SA	ILE-DE-FRANCE MOBILITES	VINCI SA	LA BANQUE POSTALE H.L. SFH SA	FAURECIA SE	SCHNEIDER ELECTRIC SE	CAISSE NATIONALE DE R.M. AGR G.	ORPEA SA	ALD SA	NERVAL SAS
k_0	0.00367	1.23178	0.68374	0.69159	2.32236	1.34388	0.82438	1.41793	0.00727	0.05455
θ_0	3.20289	0.07137	0.17473	0.00001	2.86489	0.58759	0.51699	3.70027	0.01172	0.00464
σ_0	1.42826	0.38687	0.08999	1.26949	0.02106	1.01145	0.29950	0.70012	0.00983	0.00000
γ_{0,t_0}	0.24506	0.28040	0.08984	0.00000	4.01694	1.10654	0.00249	7.47861	0.07894	0.30763
$\beta_{Eastw.Wind}$	–	–	–	–	–	–	–	–	–	–
$\beta_{Drought}$	–	–	–	0.00001	2.61576	–	1.52572	0.32663	–	–
β_{Flood}	0.00122	–	–	–	–	–	–	–	0.00014	–
β_{FWI}	–	0.04145	0.07551	–	–	–	–	–	–	–
$\beta_{Northw.Wind}$	–	–	–	–	–	–	–	–	–	–
$\beta_{Temp.}$	0.19624	–	–	–	–	0.69743	–	–	–	0.00813

Table 6
Long-range climate impact on relevant Italian issuers.

	AEROPORTI DI ROMA SPA	ALPERIA SPA	ASSICURAZIONI GENERALI SPA	BANCO BPM SPA
Eastw. Wind	–	–	–	–
Drought	–	–	–	0.33658
Flood	1.74705	0.00079	0.02201	0.41191
FWI	2.38446	–	–	–
Northw. Wind	0.25950	–	–	–

Table 7
Long-range climate impact on relevant German issuers.

	COMMERZ BANK AG	EURO GRID GMBH	EUSOLAG EUROPEAN SOLAR AG	LANDES BANK BADEN WUERT-TEMBERG	MUENCH. HYPO THEKEN BANK EG	RWE AG
Eastw. Wind	–	0.01782	–	–	–	0.03875
Drought	–	–	–	0.01047	0.04942	–
Flood	1.98820	–	–	–	–	–
FWI	–	–	–	–	–	–
Northw. Wind	–	–	0.21842	–	–	–

Table 8
Long-range climate impact on relevant French issuers.

	BPCE SA	ILE-DE-FRANCE MOBILITES	VINCI SA	LA BANQUE POSTALE H.L. SFH SA	FAURECIA SE	SCHNEIDER ELECTRIC SE	CAISSE NATIONALE DE R.M. AGR G.	ORPEA SA	ALD SA	NERVAL SAS
Eastw. Wind	–	–	–	–	–	–	–	–	–	–
Drought	–	–	–	0.00001	2.69371	–	1.57118	0.33637	–	–
Flood	0.00127	–	–	–	–	–	–	–	0.00014	–
FWI	–	0.17162	0.31269	–	–	–	–	–	–	–
Northw. Wind	–	–	–	–	–	–	–	–	–	–
Temperature	0.55024	–	–	–	–	1.95555	–	–	–	0.02281

Table B.9
AEROPORTI DI ROMA SPA (1% Sign. Level).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coefficient		0.00944		0.00861	0.00522
Avg. Age (S)		2.23836		2.23836	2.23836
Avg. Age (NS)	2.23836		2.23836		
Avg. Res. Maturity (S)		5.93699		5.93699	5.93699
Avg. Res. Maturity (NS)	5.93699		5.93699		
Avg. Bid–Ask Spread (S)		0.00033		0.00033	0.00033
Avg. Bid–Ask Spread (NS)	0.00033		0.00033		
Nr. (S)	0	1	0	1	1
Total Nr.	1	1	1	1	1
Non-green bonds	**Eastw. wind**	**Northw. wind**	**Drought**	**Flood**	**FWI**
Avg. Coefficient		0.01244	0.00652	0.00757	0.00390
Avg. Age (S)		1.83014	1.83014	3.77808	1.83014
Avg. Age (NS)	3.77808	5.72603	5.72603		5.72603
Avg. Res. Maturity (S)		8.42466	8.42466	6.35205	8.42466
Avg. Res. Maturity (NS)	6.35205	4.27945	4.27945		4.27945
Avg. Bid–Ask Spread (S)		0.00004	0.00004	0.28684	0.00004
Avg. Bid–Ask Spread (NS)	0.28684	0.57363	0.57363		0.57363
Nr. (S)	0	1	1	2	1
Total Nr.	2	2	2	2	2

Table B.10
ASSICURAZIONI GENERALI SPA (5% Sign. Level).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coefficient				0.06453	0.36105
Avg. Age (S)				3.01781	0.64658
Avg. Age (NS)	2.22740	2.22740	2.22740	0.64658	3.01781
Avg. Res. Maturity (S)				7.98904	9.36164
Avg. Res. Maturity (NS)	8.44658	8.44658	8.44658	9.36164	7.98904
Avg. Bid–Ask Spread (S)				0.00817	0.00655
Avg. Bid–Ask Spread (NS)	0.00763	0.00763	0.00763	0.00655	0.00817
Nr. (S)	0	0	0	2	1
Total Nr.	3	3	3	3	3
Non-green bonds	**Eastw. wind**	**Northw. wind**	**Drought**	**Flood**	**FWI**
Avg. Coefficient				0.05704	0.03478
Avg. Age (S)				2.87260	5.35479
Avg. Age (NS)	5.90548	5.90548	5.90548	8.93836	6.45616
Avg. Res. Maturity (S)				7.63562	5.44932
Avg. Res. Maturity (NS)	5.00205	5.00205	5.00205	2.36849	4.55479
Avg. Bid–Ask Spread (S)				0.11489	0.32856
Avg. Bid–Ask Spread (NS)	0.16451	0.16451	0.16451	0.21413	0.00045
Nr. (S)	0	0	0	2	2
Total Nr.	4	4	4	4	4

Table B.11
ALPERIA SPA (5% Sign. Level).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coefficient		0.00783	0.04267	0.03607	0.02434
Avg. Age (S)		2.98082	2.98082	2.98082	1.95068
Avg. Age (NS)	2.63744	2.46575	1.95068	1.95068	2.98082
Avg. Res. Maturity (S)		1.33425	0.83562	0.83562	3.82192
Avg. Res. Maturity (NS)	1.83105	2.07945	3.82192	3.82192	0.83562
Avg. Bid–Ask Spread (S)		0.01049	0.01103	0.01103	0.00362
Avg. Bid–Ask Spread (NS)	0.00856	0.00760	0.00362	0.00362	0.01103
Nr. (S)	0	1	2	2	1
Total Nr.	3	3	3	3	3

Table B.12
BANCO BPM SPA (5% Sign. Level).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coefficient	0.06572	0.06809	0.58169	0.42894	0.38815
Avg. Age (S)	0.57260	0.57260	0.45753	0.45753	0.45753
Avg. Age (NS)	0.70274	0.70274	0.76027	0.76027	0.76027
Avg. Res. Maturity (S)	3.39452	3.39452	3.54521	3.54521	3.54521
Avg. Res. Maturity (NS)	3.79589	3.79589	3.72055	3.72055	3.72055
Avg. Bid–Ask Spread (S)	0.00511	0.00511	0.00189	0.00189	0.00189
Avg. Bid–Ask Spread (NS)	0.00004	0.00004	0.00354	0.00354	0.00354
Nr. (S)	1	1	1	1	1
Total Nr.	3	3	3	3	3
Non-green bonds	**Eastw. wind**	**Northw. wind**	**Drought**	**Flood**	**FWI**
Avg. Coefficient	0.01309	0.01879	0.05396	0.01780	
Avg. Age (S)	1.62192	3.69041	5.20000	5.64623	
Avg. Age (NS)	5.32162	5.23169	5.15662	4.92808	5.16747
Avg. Res. Maturity (S)	3.38082	1.31507	1.65708	4.10925	
Avg. Res. Maturity (NS)	2.80762	2.89744	3.22298	2.19264	2.83151
Avg. Bid–Ask Spread (S)	0.00011	0.00017	0.00023	0.00012	
Avg. Bid–Ask Spread (NS)	0.06918	0.06918	0.08960	0.10151	0.06616
Nr. (S)	1	1	6	8	0
Total Nr.	24	24	24	24	24

5. Conclusions

In the present work, we have proposed an analysis of the German, French, and Italian corporate bond markets, restricting the selection to the companies which have issued green bonds. We have evaluated the impact on corporate 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.

For now, we have focused our analysis on the most relevant issuers, identified as those that are affected by climate risk in a statistically significant way for a majority of their outstanding bonds. No issuer satisfied these criteria for the transition risk proxy, i.e. the log-returns of EU carbon allowances, as the significant relationships were sparse, among issuers, and discordant. This is in line with the findings in Livieri et al. (2023), who analyzed credit default swaps and a different set of bonds. As for the exposures to physical risk, we have found that the subset of relevant issuers can be classified into three groups, depending on the relationship of their green and non-green bonds with the physical risk variables. For the first group of issuers, physical risk variables are statistically significant and increase their spreads, but only of their non-green bonds. In contrast, their green bonds provide a hedge against physical climate risk. For the second group of issuers, green and non-green bonds have a comparable relationship with the climate risk proxy of interest, in terms of sign of the coefficient and of number of

Table B.13
EUROGRID GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.	0.0578				−0.1673
Avg. Age (S)	1.3137				2.1479
Avg. Age (NS)		1.3137	1.3137	1.3137	0.4795
Avg. Res. Maturity (S)	8.8726				9.2192
Avg. Res. Maturity (NS)		8.8726	8.8726	8.8726	8.5260
Avg. Bid–Ask Spread (S)	0.0135				0.0052
Avg. Bid–Ask Spread (NS)		0.0135	0.0135	0.0135	0.0218
Nr. of (S) Bonds	2	0	0	0	1
Total Nr. of Bonds	2	2	2	2	2
Non-green bonds:					
Avg. Coeff.	0.0112				
Avg. Age (S)	2.1479				
Avg. Age (NS)	2.0502	2.0991	2.0991	2.0991	2.0991
Avg. Res. Maturity (S)	2.7032				
Avg. Res. Maturity (NS)	11.8621	7.2826	7.2826	7.2826	7.2826
Avg. Bid–Ask Spread (S)	0.0787				
Avg. Bid–Ask Spread (NS)	0.5750	0.3268	0.3268	0.3268	0.3268
Nr. of (S) Bonds	3	0	0	0	0
Total Nr. of Bonds	6	6	6	6	6

Table B.14
COMMERZBANK AG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	2.1479	2.1479	2.1479	2.1479	2.1479
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	0.6521	0.6521	0.6521	0.6521	0.6521
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0007	0.0007	0.0007	0.0007	0.0007
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1
Non-green bonds:					
Avg. Coeff.	0.0239	0.0108		0.0024	−0.0097
Avg. Age (S)	2.1479	2.1479		2.1479	2.1479
Avg. Age (NS)	2.0596	2.0596	2.0722	1.9965	2.0516
Avg. Res. Maturity (S)	20.8068	1.2233		12.9115	7.6612
Avg. Res. Maturity (NS)	6.5973	9.8612	8.6272	4.3429	8.8907
Avg. Bid–Ask Spread (S)	0.6568	0.2112		0.2503	0.0010
Avg. Bid–Ask Spread (NS)	0.0796	0.1539	0.1621	0.0739	0.2060
Nr. of (S) Bonds	2	2	0	7	3
Total Nr. of Bonds	14	14	14	14	14

Table B.15
EUSOLAG EUROPEAN SOLAR AG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.	−0.0330	0.0387			−0.0322
Avg. Age (S)	0.8932	0.8932			0.8932
Avg. Age (NS)			0.8932	0.8932	
Avg. Res. Maturity (S)	4.0849	4.0849			4.0849
Avg. Res. Maturity (NS)			4.0849	4.0849	
Avg. Bid–Ask Spread (S)	0.3976	0.3976			0.3976
Avg. Bid–Ask Spread (NS)			0.3976	0.3976	
Nr. of (S) Bonds	1	1	0	0	1
Total Nr. of Bonds	1	1	1	1	1

Table B.16
RECONCEPT GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.				−0.0600	
Avg. Age (S)				2.1479	
Avg. Age (NS)	1.6178	1.6178	1.6178	1.0877	1.6178
Avg. Res. Maturity (S)				2.4904	
Avg. Res. Maturity (NS)	3.7014	3.7014	3.7014	4.9123	3.7014
Avg. Bid–Ask Spread (S)				0.0085	
Avg. Bid–Ask Spread (NS)	0.0115	0.0115	0.0115	0.0145	0.0115
Nr. of (S) Bonds	0	0	0	1	0
Total Nr. of Bonds	2	2	2	2	2

Table B.17
RWE AG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.	0.0448	0.0403	0.0083	−0.0163	−0.0628
Avg. Age (S)	0.7644	0.7644	0.7644	0.7644	0.9279
Avg. Age (NS)	1.4082	1.4082	1.2473	1.2473	1.4849
Avg. Res. Maturity (S)	5.2397	5.2397	3.2384	3.2384	5.4100
Avg. Res. Maturity (NS)	8.2648	8.2648	8.0089	8.0089	9.5219
Avg. Bid–Ask Spread (S)	0.0193	0.0193	0.0160	0.0160	0.0150
Avg. Bid–Ask Spread (NS)	0.0031	0.0031	0.0080	0.0080	0.0013
Nr. of (S) Bonds	2	2	1	1	3
Total Nr. of Bonds	5	5	5	5	5
Non-green bonds:					
Avg. Coeff.	0.0290				
Avg. Age (S)	2.1479				
Avg. Age (NS)	0.5123	1.3301	1.3301	1.3301	1.3301
Avg. Res. Maturity (S)	14.6712				
Avg. Res. Maturity (NS)	2.4904	8.5808	8.5808	8.5808	8.5808
Avg. Bid–Ask Spread (S)	0.0008				
Avg. Bid–Ask Spread (NS)	0.4520	0.2264	0.2264	0.2264	0.2264
Nr. of (S) Bonds	1	0	0	0	0
Total Nr. of Bonds	2	2	2	2	2

Table B.18
MUENCHENER HYPOTHEKENBANK EG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.	−0.0401	0.0236	0.0015		−0.0657
Avg. Age (S)	1.8575	2.1479	2.0899		1.9525
Avg. Age (NS)	1.8822	1.8407	1.5279	1.8791	1.8351
Avg. Res. Maturity (S)	13.1425	7.3068	8.1989		6.8630
Avg. Res. Maturity (NS)	6.8720	7.7057	6.7507	7.6558	8.1315
Avg. Bid–Ask Spread (S)		0.0007	0.0022		0.0100
Avg. Bid–Ask Spread (NS)	0.0036	0.0042	0.0094	0.0036	0.0028
Nr. of (S) Bonds	1	1	5	0	3
Total Nr. of Bonds	8	8	8	8	8

Table B.19
LANDESBANK BADEN WUERTTEMBERG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.	0.0134	−0.0078	0.0333	−0.0136	−0.0394
Avg. Age (S)	1.7244	1.7803	1.8579	1.6251	1.9687
Avg. Age (NS)	1.8787	1.8643	1.8549	1.8938	1.8210
Avg. Res. Maturity (S)	5.1505	5.1252	5.7435	6.6703	4.6808
Avg. Res. Maturity (NS)	5.5322	5.5143	5.2822	5.2816	5.7245
Avg. Bid–Ask Spread (S)	0.0005	0.0136	0.0150	0.2006	0.0123
Avg. Bid–Ask Spread (NS)	0.0363	0.0327	0.0425	0.0030	0.0367
Nr. of (S) Bonds	24	16	69	23	39
Total Nr. of Bonds	164	164	164	164	164
Non-green bonds:					
Avg. Coeff.	−0.0010	−0.0218	0.0086	−0.0479	−0.0183
Avg. Age (S)	1.9445	1.9918	2.0317	2.1479	2.0699
Avg. Age (NS)	2.1280	2.1080	2.1255	2.0959	2.1067
Avg. Res. Maturity (S)	3.4801	1.0904	6.7824	7.7162	3.9918
Avg. Res. Maturity (NS)	8.0786	7.6984	7.6903	7.4409	7.7262
Avg. Bid–Ask Spread (S)	0.0002	0.0002	0.0012	0.0017	0.0000
Avg. Bid–Ask Spread (NS)	0.0215	0.0193	0.0238	0.0220	0.0200
Nr. of (S) Bonds	4	1	7	5	2
Total Nr. of Bonds	31	31	31	31	31

Table B.20
EEW ENERGY FROM WASTE GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	1.6630	1.6630	1.6630	1.6630	1.6630
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	3.3397	3.3397	3.3397	3.3397	3.3397
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0004	0.0004	0.0004	0.0004	0.0004
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.21
GREENCELLS GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	2.1479	2.1479	2.1479	2.1479	2.1479
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	2.7836	2.7836	2.7836	2.7836	2.7836
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0203	0.0203	0.0203	0.0203	0.0203
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.22
HAMBURGER HOCHBAHN AG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	2.0082	2.0082	2.0082	2.0082	2.0082
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	7.9973	7.9973	7.9973	7.9973	7.9973
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0042	0.0042	0.0042	0.0042	0.0042
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.23
DZ HYP AG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	1.0137	1.0137	1.0137	1.0137	1.0137
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	6.7370	6.7370	6.7370	6.7370	6.7370
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0031	0.0031	0.0031	0.0031	0.0031
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.24
BAYWA AG (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	2.1479	2.1479	2.1479	2.1479	2.1479
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	1.3288	1.3288	1.3288	1.3288	1.3288
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0038	0.0038	0.0038	0.0038	0.0038
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.25
AOC I DIE STADTENTWICKLER GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	0.8795	0.8795	0.8795	0.8795	0.8795
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	4.1123	4.1123	4.1123	4.1123	4.1123
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.1751	0.1751	0.1751	0.1751	0.1751
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

significant relationships. As for the third group of issuers, they only have green bonds outstanding. The spreads of those bonds tend to be reduced by some of the physical climate risk proxies, or are unaffected, thus providing a hedge against physical climate risk.

In the final part of this work, we have proposed an extended intensity-based model for pricing risky coupon bonds, which includes explicit external factors, in the hazard rate, to represent the physical risk variables. We have calibrated the model on the data, based on the issuers and the variables of interest identified in the first portion of the analysis. Results differ by country: all relevant Italian issuers are exposed to the flood risk indicator, with the airport being the most negatively affected. As for the relevant German firms, the resulting risk factors are divided by industry: the most frequent is the deseasonalized average daily wind speed, which exclusively affects renewable energy producers. On the other hand, all German banks in the relevant sample are exposed to either drought or flood risk. This final phenomenon also

Table B.26
MOMOX HOLDING GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	2.1479	2.1479	2.1479	2.1479	2.1479
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	2.3671	2.3671	2.3671	2.3671	2.3671
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0064	0.0064	0.0064	0.0064	0.0064
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.27
PROCREDIT HOLDING AG & CO KGAA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	2.1479	2.1479	2.1479	2.1479	2.1479
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	0.2493	0.2493	0.2493	0.2493	0.2493
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0037	0.0037	0.0037	0.0037	0.0037
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.28
NOVELIS SHEET INGOT GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	1.9123	1.9123	1.9123	1.9123	1.9123
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	6.1342	6.1342	6.1342	6.1342	6.1342
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)	0.0051	0.0051	0.0051	0.0051	0.0051
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

Table B.29
MBT SYSTEMS GMBH (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Drought	Flood	FWI
Avg. Coeff.					
Avg. Age (S)					
Avg. Age (NS)	1.6411	1.6411	1.6411	1.6411	1.6411
Avg. Res. Maturity (S)					
Avg. Res. Maturity (NS)	4.3616	4.3616	4.3616	4.3616	4.3616
Avg. Bid–Ask Spread (S)					
Avg. Bid–Ask Spread (NS)					
Nr. of (S) Bonds	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1

emerges in the French case, in which drought and temperature are the most important climate variables, and all banks are impacted by either drought or flood risk.

These findings highlight how climate risk differs across companies, sectors, countries, and bond types. For a number of companies, green bonds provide greater resilience in the face of climate risk, suggesting that markets may recognize and reward their climate-aligned features. Hopefully, this study contributes to the growing understanding of how climate risks manifest in financial markets. From a policy perspective, the findings support the case for incorporating granular climate data into credit risk assessments. Supervisors, rating agencies, and institutional investors may benefit from tailoring their methodologies to capture issuer-specific sensitivities, particularly in the context of climate-related stress testing or scenario analysis.

Future extensions of this work could follow multiple paths. Firstly, the issuer sample could be expanded to include a wider range of firms and countries, enhancing robustness and extendability of the results. Moreover, transition risk – which did not have a significant impact, with the proxies used in this study – could be investigated through different potential measures. Among them are also forward-looking transition risk indicators, such as firm-level emissions pathways or technology adoption scenarios, which could provide a richer understanding of market pricing dynamics. Overall, what emerges from this work is the potential of green bonds to hedge certain physical risks and the persistent complexity in climate risk pricing. As markets and regulatory frameworks evolve, the interplay between climate and credit risk will be increasingly important for financial research and practice.

CRediT authorship contribution statement

Nicola Bartolini: Writing – original draft, Validation, Software, Methodology, Formal analysis. **Silvia Romagnoli:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Amia Santini:** Writing – original draft, Methodology, Conceptualization, Software, Formal analysis, Data curation.

Table B.30
ALD SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	0.6493	0.6493	0.6493	0.6493	0.6493	0.6493
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	4.3534	4.3534	4.3534	4.3534	4.3534	4.3534
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1
Non-green bonds:						
Avg. Coeff.	0.0142			0.2057	0.0437	
Avg. Age (S)	2.3589			0.3753	1.5817	
Avg. Age (NS)	1.7479	1.8701	1.8701	2.2438	2.3027	1.8701
Avg. Res. Maturity (S)	0.6411			2.6274	1.4192	
Avg. Res. Maturity (NS)	1.7534	1.5310	1.5310	1.2568	1.6986	1.5310
Avg. Bid–Ask Spread (S)	0.0004			0.3955	0.1504	
Avg. Bid–Ask Spread (NS)	0.1128	0.0902	0.0902	0.0138	0.0003	0.0902
Nr. of (S) Bonds	1	0	0	1	3	0
Total Nr. of Bonds	5	5	5	5	5	5

Table B.31
ORPEA SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	1.9096	1.9096	1.9096	1.9096	1.9096	1.9096
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	5.0959	5.0959	5.0959	5.0959	5.0959	5.0959
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0727	0.0727	0.0727	0.0727	0.0727	0.0727
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1
Non-green bonds:						
Avg. Coeff.	−0.0008	0.0003	−0.0003	0.0020	0.0004	
Avg. Age (S)	4.6658	4.8438	4.6658	4.2831	4.9781	
Avg. Age (NS)	5.1457	5.0863	5.1457	5.4712	5.0325	5.0257
Avg. Res. Maturity (S)	2.0274	1.9164	2.0274	2.6804	2.0329	
Avg. Res. Maturity (NS)	4.0379	4.0749	4.0379	4.0482	3.7499	3.5353
Avg. Bid–Ask Spread (S)	0.0035	0.0037	0.0035	0.0034	0.0053	
Avg. Bid–Ask Spread (NS)	0.0984	0.0984	0.0984	0.1174	0.0846	0.0747
Nr. of (S) Bonds	2	2	2	3	1	0
Total Nr. of Bonds	8	8	8	8	8	8

Table B.32
CAISSE NATIONALE DE REASSURANCE MUTUELLE AGR GROUPAMA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.				0.0055		
Avg. Age (S)				1.6438		
Avg. Age (NS)	1.6438	1.6438	1.6438		1.6438	1.6438
Avg. Res. Maturity (S)				5.3616		
Avg. Res. Maturity (NS)	5.3616	5.3616	5.3616		5.3616	5.3616
Avg. Bid–Ask Spread (S)				0.0057		
Avg. Bid–Ask Spread (NS)	0.0057	0.0057	0.0057		0.0057	0.0057
Nr. of (S) Bonds	0	0	0	1	0	0
Total Nr. of Bonds	1	1	1	1	1	1
Non-green bonds:						
Avg. Coeff.				0.0256	−0.0139	
Avg. Age (S)				6.0986	3.4521	
Avg. Age (NS)	4.6603	4.6603	4.6603	3.9411	5.2644	4.6603
Avg. Res. Maturity (S)				3.9068	6.5562	
Avg. Res. Maturity (NS)	5.3470	5.3470	5.3470	6.0671	4.7425	5.3470
Avg. Bid–Ask Spread (S)				0.5974	0.0003	
Avg. Bid–Ask Spread (NS)	0.1993	0.1993	0.1993	0.0002	0.2988	0.1993
Nr. of (S) Bonds	0	0	0	1	1	0
Total Nr. of Bonds	3	3	3	3	3	3

Table B.33
SCHNEIDER ELECTRIC SE (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	7.3616	7.3616	7.3616	7.3616	7.3616	7.3616
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	2.6274	2.6274	2.6274	2.6274	2.6274	2.6274
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0017	0.0017	0.0017	0.0017	0.0017	0.0017
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1
Non-green bonds:						
Avg. Coeff.	0.0285	−0.0344	0.0374	−0.0077	−0.0051	
Avg. Age (S)	2.9671	2.9671	2.9274	2.8877	4.1205	
Avg. Age (NS)	4.9178	4.9178	5.5945	4.9377	4.6295	4.5277
Avg. Res. Maturity (S)	6.0384	6.0384	5.0767	4.1151	4.8849	
Avg. Res. Maturity (NS)	3.8377	3.8377	3.7452	4.3185	4.1260	4.2778
Avg. Bid–Ask Spread (S)	0.0006	0.0006	0.1755	0.3504	0.0004	
Avg. Bid–Ask Spread (NS)	0.1416	0.1416	0.0720	0.0542	0.1417	0.1134
Nr. of (S) Bonds	1	1	2	1	1	0
Total Nr. of Bonds	5	5	5	5	5	5

Table B.34
FAURECIA SE (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						−0.0343
Avg. Age (S)						1.9288
Avg. Age (NS)	1.9288	1.9288	1.9288	1.9288	1.9288	
Avg. Res. Maturity (S)						6.3014
Avg. Res. Maturity (NS)	6.3014	6.3014	6.3014	6.3014	6.3014	
Avg. Bid–Ask Spread (S)						0.0054
Avg. Bid–Ask Spread (NS)	0.0054	0.0054	0.0054	0.0054	0.0054	
Nr. of (S) Bonds	0	0	0	0	0	1
Total Nr. of Bonds	1	1	1	1	1	1
Non-green bonds:						
Avg. Coeff.	0.1867		−0.0526	0.1126		−0.0981
Avg. Age (S)	0.2849		1.2986	0.7918		0.2849
Avg. Age (NS)	3.2071	2.7201	3.0044	3.6842	2.7201	3.2071
Avg. Res. Maturity (S)	3.2986		3.9699	3.6342		3.2986
Avg. Res. Maturity (NS)	3.8334	3.7443	3.6992	3.7993	3.7443	3.8334
Avg. Bid–Ask Spread (S)	0.0006		0.5618	0.2806		0.0006
Avg. Bid–Ask Spread (NS)	0.4304	0.3586	0.3179	0.3976	0.3586	0.4304
Nr. of (S) Bonds	1	0	1	2	0	1
Total Nr. of Bonds	6	6	6	6	6	6

Table B.35
LA BANQUE POSTALE HOME LOAN SFH SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.			−0.0374	0.0343		
Avg. Age (S)			0.7973	0.7973		
Avg. Age (NS)	0.7973	0.7973			0.7973	0.7973
Avg. Res. Maturity (S)			7.2082	7.2082		
Avg. Res. Maturity (NS)	7.2082	7.2082			7.2082	7.2082
Avg. Bid–Ask Spread (S)			0.0039	0.0039		
Avg. Bid–Ask Spread (NS)	0.0039	0.0039			0.0039	0.0039
Nr. of (S) Bonds	0	0	1	1	0	0
Total Nr. of Bonds	1	1	1	1	1	1

Acknowledgments

The authors wish to thank the reviewers for their constructive comments, which have led to a much improved version of the work. They also wish to thank the participants and the discussant of the 9th Energy Finance Italia Workshop for their insightful feedback, which contributed to the refinement of this work. Any errors or shortcomings in the content of this paper are solely the responsibility of the authors. The authors also acknowledge funding from the European Union - NextGenerationEU through the Italian Ministry of University and Research under the National Recovery and Resilience Plan (PNRR) - Mission 4 Education and research - Component 2 From research to business - Investment 1.1 Notice Prin 2022 - DD N. 104 of 2/2/2022, title [Just Energy Transition – JET: Stochastic and machine learning methods for the evaluation, mitigation and geographical hedging of involved natural risks (with climate in view)], proposal code [P2022XTLM2] - CUP [J53D23015530001].

Appendix A. Mathematical formulation of intensity based models

In this section, we report the main theoretical results, developed by Duffie and Singleton (1999) for the intensity-based models, that allow us to recover the pricing formula in Eq. (12) as a particular case. An extended exposition of this methodology can be found in Bielecki and Rutkwski (2004) and McNeil et al. (2015).

Table B.36
VINCI SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.					−0.0931	
Avg. Age (S)					2.2521	
Avg. Age (NS)	2.2521	2.2521	2.2521	2.2521		2.2521
Avg. Res. Maturity (S)					5.7534	
Avg. Res. Maturity (NS)	5.7534	5.7534	5.7534	5.7534		5.7534
Avg. Bid–Ask Spread (S)					0.0033	
Avg. Bid–Ask Spread (NS)	0.0033	0.0033	0.0033	0.0033		0.0033
Nr. of (S) Bonds	0	0	0	0	1	0
Total Nr. of Bonds	1	1	1	1	1	1
Non-green bonds:						
Avg. Coeff.		−0.0268	−0.1517	0.1804	−0.1508	0.0318
Avg. Age (S)		4.4247	0.3644	0.3644	1.6384	2.3945
Avg. Age (NS)	2.9929	2.6349	3.6500	3.6500	3.3315	3.3918
Avg. Res. Maturity (S)		7.5836	9.6438	9.6438	8.8712	8.6137
Avg. Res. Maturity (NS)	6.9151	6.7479	6.2329	6.2329	6.4260	5.7826
Avg. Bid–Ask Spread (S)		0.0000	0.0012	0.0012	0.0009	0.0006
Avg. Bid–Ask Spread (NS)	0.0825	0.1032	0.1029	0.1029	0.1030	0.1372
Nr. of (S) Bonds	0	1	1	1	1	2
Total Nr. of Bonds	5	5	5	5	5	5

Table B.37
NERVAL SAS (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.	−0.0722	−0.1413	0.1319			
Avg. Age (S)	0.8740	0.6082	0.6082			
Avg. Age (NS)	0.6082	0.8740	0.8740	0.7411	0.7411	0.7411
Avg. Res. Maturity (S)	9.1342	5.3973	5.3973			
Avg. Res. Maturity (NS)	5.3973	9.1342	9.1342	7.2658	7.2658	7.2658
Avg. Bid–Ask Spread (S)	0.0038	0.0034	0.0034			
Avg. Bid–Ask Spread (NS)	0.0034	0.0038	0.0038	0.0036	0.0036	0.0036
Nr. of (S) Bonds	1	1	1	0	0	0
Total Nr. of Bonds	2	2	2	2	2	2

Table B.38
COVIVIO SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.	−0.0077					
Avg. Age (S)	3.4493					
Avg. Age (NS)	6.7781	5.1137	5.1137	5.1137	5.1137	5.1137
Avg. Res. Maturity (S)	8.5589					
Avg. Res. Maturity (NS)	3.2274	5.8932	5.8932	5.8932	5.8932	5.8932
Avg. Bid–Ask Spread (S)	0.0074					
Avg. Bid–Ask Spread (NS)	0.0017	0.0029	0.0029	0.0029	0.0029	0.0029
Nr. of (S) Bonds	1	0	0	0	0	0
Total Nr. of Bonds	2	2	2	2	2	2
Non-green bonds:						
Avg. Coeff.	−0.0106	0.0037		−0.0022		
Avg. Age (S)	4.1863	5.3671		5.3671		
Avg. Age (NS)	5.1945	4.4648	4.6904	4.4648	4.6904	4.6904
Avg. Res. Maturity (S)	5.8192	1.6384		1.6384		
Avg. Res. Maturity (NS)	3.3110	5.5406	4.5651	5.5406	4.5651	4.5651
Avg. Bid–Ask Spread (S)	0.0000	0.0001		0.0001		
Avg. Bid–Ask Spread (NS)	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
Nr. of (S) Bonds	2	1	0	1	0	0
Total Nr. of Bonds	4	4	4	4	4	4

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space and let $\mathcal{F}_t = \sigma(\{\psi_t : s \leq t\})$ be the filtration generated by some observed background process. Define the random time τ on $\mathcal{F}$, with $\tau > 0$ a.s., and denote by $Y_t = 1_{\{\tau \leq t\}}$ the associated jump indicator and by $\mathcal{H}_t = \sigma\{1_{\{\tau \leq s\}} : s \leq t\}$ the filtration generated by Y_t. Then, for our purposes, define the general filtration as

$$\mathcal{G}_t = \mathcal{F}_t \vee \mathcal{H}_t,$$

where τ is a stopping time with respect to $\mathcal{G}_t$ and $\mathcal{H}_t$, but not necessarily with respect to $\mathcal{F}_t$.

Definition A.1. Doubly stochastic random time

A random time τ is said to be doubly stochastic if there exists a positive $\mathcal{F}_t$-adapted process γ_t, such that $\Gamma_t = \int_0^t \gamma_s ds$ is strictly increasing and finite for every $t > 0$ and such that, for all $t \geq 0$,

$$P(\tau > t | \mathcal{F}_\infty) = e^{-\int_0^t \gamma_s ds}. \tag{A.1}$$

In such a case, γ_t is referred to as the $\mathcal{F}_t$-conditional hazard process of τ.

Lemma A.1. *For every $t \leq 0$, the following statement holds:*

$$\mathcal{G}_t^* = \{A \in \mathcal{G}_t : \exists B \in \mathcal{F}_t, A \cap \{\tau > t\} = B \cap \{\tau > t\}\}.$$

This lemma states that, before the default time, the only known events are those related to the background filtration $\mathcal{F}_t$, from which derives the following lemma.

Table B.39
ILE-DE-FRANCE MOBILITES (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.			−0.0519		−0.0439	
Avg. Age (S)			1.2603		1.7534	
Avg. Age (NS)	1.3677	1.3677	1.3945	1.3677	1.2712	1.3677
Avg. Res. Maturity (S)			13.7507		8.2521	
Avg. Res. Maturity (NS)	13.6433	13.6433	13.6164	13.6433	14.9911	13.6433
Avg. Bid–Ask Spread (S)			0.0045		0.0031	
Avg. Bid–Ask Spread (NS)	0.0020	0.0020	0.0036	0.0020	0.0032	0.0020
Nr. of (S) Bonds	0	0	1	0	1	0
Total Nr. of Bonds	5	5	5	5	5	5
Non-green bonds:						
Avg. Coeff.			−0.1218	−0.1554	−0.1443	0.2928
Avg. Age (S)			0.5123	0.5123	0.5123	0.5123
Avg. Age (NS)	2.2256	2.2256	3.0822	3.0822	3.0822	3.0822
Avg. Res. Maturity (S)			29.0082	29.0082	29.0082	29.0082
Avg. Res. Maturity (NS)	17.6603	17.6603	11.9863	11.9863	11.9863	11.9863
Avg. Bid–Ask Spread (S)			0.0002	0.0002	0.0002	0.0002
Avg. Bid–Ask Spread (NS)	0.1584	0.1584	0.2377	0.2377	0.2377	0.2377
Nr. of (S) Bonds	0	0	1	1	1	1
Total Nr. of Bonds	3	3	3	3	3	3

Table B.40
BANQUE FEDERATIVE DU CREDIT MUTUEL SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.		−0.0254	−0.0236			
Avg. Age (S)		1.6658	1.6658			
Avg. Age (NS)	2.0274	2.3890	2.3890	2.0274	2.0274	2.0274
Avg. Res. Maturity (S)		5.3397	5.3397			
Avg. Res. Maturity (NS)	4.9767	4.6137	4.6137	4.9767	4.9767	4.9767
Avg. Bid–Ask Spread (S)		0.0061	0.0061			
Avg. Bid–Ask Spread (NS)	0.0061	0.0060	0.0060	0.0061	0.0061	0.0061
Nr. of (S) Bonds	0	1	1	0	0	0
Total Nr. of Bonds	2	2	2	2	2	2
Non-green bonds:						
Avg. Coeff.	0.0125	−0.0301	−0.1302	0.0708	0.0059	0.0869
Avg. Age (S)	5.8132	4.2482	1.0890	4.6315	3.1202	3.3920
Avg. Age (NS)	4.4690	4.6016	4.8063	4.5701	4.7817	4.8467
Avg. Res. Maturity (S)	5.6460	4.7490	8.2103	8.8671	5.2644	5.4566
Avg. Res. Maturity (NS)	4.8049	4.8809	4.6479	4.6042	4.8143	4.7354
Avg. Bid–Ask Spread (S)	0.0003	0.1098	0.1377	0.1004	0.0735	0.0695
Avg. Bid–Ask Spread (NS)	0.1329	0.1233	0.1211	0.1233	0.1294	0.1349
Nr. of (S) Bonds	5	5	4	4	8	12
Total Nr. of Bonds	64	64	64	64	64	64

Table B.41
BPCE SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.			0.0104	−0.0033	0.0243	−0.0144
Avg. Age (S)			2.1781	3.2356	1.1205	1.1205
Avg. Age (NS)	2.1781	2.1781		1.1205	3.2356	3.2356
Avg. Res. Maturity (S)			5.3274	1.7699	8.8849	8.8849
Avg. Res. Maturity (NS)	5.3274	5.3274		8.8849	1.7699	1.7699
Avg. Bid–Ask Spread (S)			0.0038	0.0012	0.0064	0.0064
Avg. Bid–Ask Spread (NS)	0.0038	0.0038		0.0064	0.0012	0.0012
Nr. of (S) Bonds	0	0	2	1	1	1
Total Nr. of Bonds	2	2	2	2	2	2
Non-green bonds:						
Avg. Coeff.	−0.0068	0.0442	−0.0573	0.2726	0.2110	−0.0140
Avg. Age (S)	3.2258	1.7586	4.2773	1.9538	1.7787	4.6830
Avg. Age (NS)	4.8568	4.9797	4.7197	4.9570	5.0244	4.6220
Avg. Res. Maturity (S)	6.3652	5.5387	3.7313	6.9288	5.2362	4.5039
Avg. Res. Maturity (NS)	4.3512	4.5054	4.7918	4.3443	4.5303	4.6785
Avg. Bid–Ask Spread (S)	0.0584	0.0009	0.0220	0.0352	0.0369	0.0700
Avg. Bid–Ask Spread (NS)	0.0912	0.0971	0.1001	0.0929	0.0936	0.0971
Nr. of (S) Bonds	10	8	13	8	9	29
Total Nr. of Bonds	77	77	77	77	77	77

Table B.42
SOCIETE DU GRAND PARIS (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.	−0.0366	−0.0625	0.0038			−0.0240
Avg. Age (S)	2.9799	1.8027	2.1384			4.1493
Avg. Age (NS)	2.5045	2.6464	2.6587	2.5937	2.5937	2.3714
Avg. Res. Maturity (S)	15.7507	23.2137	37.3808			8.4507
Avg. Res. Maturity (NS)	30.2824	27.8473	26.1544	27.5577	27.5577	30.2873
Avg. Bid–Ask Spread (S)	0.0028	0.0020	0.0109			0.0002
Avg. Bid–Ask Spread (NS)	0.0081	0.0074	0.0066	0.0071	0.0071	0.0081
Nr. of (S) Bonds	3	1	2	0	0	2
Total Nr. of Bonds	16	16	16	16	16	16

Table B.43
CREDIT AGRICOLE HOME LOAN SFH SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.	−0.0286					−0.0433
Avg. Age (S)	3.2301					3.2301
Avg. Age (NS)		3.2301	3.2301	3.2301	3.2301	
Avg. Res. Maturity (S)	6.7781					6.7781
Avg. Res. Maturity (NS)		6.7781	6.7781	6.7781	6.7781	
Avg. Bid–Ask Spread (S)	0.0024					0.0024
Avg. Bid–Ask Spread (NS)		0.0024	0.0024	0.0024	0.0024	
Nr. of (S) Bonds	1	0	0	0	0	1
Total Nr. of Bonds	1	1	1	1	1	1

Table B.44
DERICHEBOURG SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	1.6795	1.6795	1.6795	1.6795	1.6795	1.6795
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	5.3836	5.3836	5.3836	5.3836	5.3836	5.3836
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0080	0.0080	0.0080	0.0080	0.0080	0.0080
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1

Table B.45
BPCE SFH SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.	−0.0324	−0.0311	−0.0245		−0.0458	−0.0796
Avg. Age (S)	1.7370	1.7370	1.7370		1.7370	2.7562
Avg. Age (NS)	1.7562	1.7562	1.7562	1.7498	1.7562	1.2466
Avg. Res. Maturity (S)	7.7699	7.7699	7.7699		7.7699	7.2493
Avg. Res. Maturity (NS)	8.2507	8.2507	8.2507	8.0904	8.2507	8.5110
Avg. Bid–Ask Spread (S)	0.0002	0.0002	0.0002		0.0002	0.0023
Avg. Bid–Ask Spread (NS)	0.0026	0.0026	0.0026	0.0017	0.0026	0.0014
Nr. of (S) Bonds	1	1	1	0	1	1
Total Nr. of Bonds	3	3	3	3	3	3

Table B.46
COMPAGNIE DE PHALSBOURG SARL (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	3.9041	3.9041	3.9041	3.9041	3.9041	3.9041
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	1.0795	1.0795	1.0795	1.0795	1.0795	1.0795
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1

Lemma A.2. *Let τ be a random time (not necessarily doubly stochastic) such that $P(\tau > t|\mathcal{F}_t) > 0$ for all $t \leq 0$, then, for every integrable random variable:*

$$\mathrm{E}[1_{\{\tau>t\}}X|\mathcal{G}_t] = 1_{\{\tau>t\}}\frac{\mathrm{E}[1_{\{\tau>t\}}X|\mathcal{F}_t]}{P(\tau > t|\mathcal{F}_t)}. \tag{A.2}$$

Corollary A.2.1. *Let $T > t$ and assume τ is doubly stochastic with hazard process γ_t, if $\tilde{X}$ is integrable and $\mathcal{F}_T$-measurable, then:*

$$\mathbb{E}\{\tilde{X}1_{\{\tau>T\}}|\mathcal{G}_t\} = 1_{\{\tau>t\}}\mathbb{E}\left[e^{-\int_t^T \gamma_s ds}\tilde{X}\middle|\mathcal{F}_t\right]. \tag{A.3}$$

Table B.47
GETLINK SE (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	2.3288	2.3288	2.3288	2.3288	2.3288	2.3288
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	2.6740	2.6740	2.6740	2.6740	2.6740	2.6740
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1

Table B.48
GECINA SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.	−0.0062	−0.0069	−0.0389	−0.0031		−0.0433
Avg. Age (S)	5.3705	5.6776	1.0904	6.4596		6.2267
Avg. Age (NS)	5.6021	5.4740	5.9280	5.0575	5.5249	5.1740
Avg. Res. Maturity (S)	7.7178	7.4402	9.9178	5.3781		3.9781
Avg. Res. Maturity (NS)	5.1661	5.5422	5.6620	6.3360	6.0167	7.0360
Avg. Bid–Ask Spread (S)	0.0060	0.0059	0.0145	0.0050		0.0009
Avg. Bid–Ask Spread (NS)	0.0023	0.0027	0.0025	0.0028	0.0035	0.0048
Nr. of (S) Bonds	4	3	1	4	0	4
Total Nr. of Bonds	12	12	12	12	12	12

Table B.49
NEOEN SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.		−0.0502	−0.0590			
Avg. Age (S)		2.7397	2.7397			
Avg. Age (NS)	1.5973	0.4548	0.4548	1.5973	1.5973	1.5973
Avg. Res. Maturity (S)		2.2630	2.2630			
Avg. Res. Maturity (NS)	3.4055	4.5479	4.5479	3.4055	3.4055	3.4055
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0125	0.0125	0.0125	0.0125	0.0125	0.0125
Nr. of (S) Bonds	0	1	1	0	0	0
Total Nr. of Bonds	2	2	2	2	2	2

Table B.50
NEW IMMO HOLDING SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	3.2411	3.2411	3.2411	3.2411	3.2411	3.2411
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	3.7479	3.7479	3.7479	3.7479	3.7479	3.7479
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0038	0.0038	0.0038	0.0038	0.0038	0.0038
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	1	1	1	1	1	1

Table B.51
SUEZ SA (FR) (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						
Avg. Age (S)						
Avg. Age (NS)	0.7644	0.7644	0.7644	0.7644	0.7644	0.7644
Avg. Res. Maturity (S)						
Avg. Res. Maturity (NS)	7.5744	7.5744	7.5744	7.5744	7.5744	7.5744
Avg. Bid–Ask Spread (S)						
Avg. Bid–Ask Spread (NS)	0.0070	0.0070	0.0070	0.0070	0.0070	0.0070
Nr. of (S) Bonds	0	0	0	0	0	0
Total Nr. of Bonds	3	3	3	3	3	3

Theorem A.3. *Suppose that, under $\mathbb{Q}$, τ is doubly stochastic with background filtration $\mathcal{F}_t$ and hazard process γ_t. Define $R_s = r_s + \gamma_s$ and assume that the following random variables are integrable with respect to $\mathbb{Q}$:*

1. $e^{-\int_t^T r_s ds}|X|$,
2. $\int_t^T |\upsilon_s| \exp\{\int_t^s r_u du\} ds$,
3. $\int_t^T |Z_s \gamma_s| \exp\{\int_t^s R_u du\} ds$,

where υ_s is a continuous dividend, Z_τ is the value of the claim at the time of the default and γ_t is the stochastic hazard rate. Then, the following hold:

$$\mathbb{E}^{\mathbb{Q}}\left[1_{\{\tau>T\}} e^{-\int_t^T r_s ds} X \middle| \mathcal{G}_t\right] = 1_{\{\tau>t\}} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_t^T R_s ds} X \middle| \mathcal{F}_t\right], \tag{A.4}$$

Table B.52
VOLTALIA SA (α = 0.05).

Green bonds	Eastw. wind	Northw. wind	Avg. temp.	Drought	Flood	FWI
Avg. Coeff.						−0.0219
Avg. Age (S)						2.1233
Avg. Age (NS)	2.1233	2.1233	2.1233	2.1233	2.1233	
Avg. Res. Maturity (S)						1.8795
Avg. Res. Maturity (NS)	1.8795	1.8795	1.8795	1.8795	1.8795	
Avg. Bid–Ask Spread (S)						0.0035
Avg. Bid–Ask Spread (NS)	0.0035	0.0035	0.0035	0.0035	0.0035	
Nr. of (S) Bonds	0	0	0	0	0	1
Total Nr. of Bonds	1	1	1	1	1	1

$$\mathbb{E}^{\mathbb{Q}}\left[\int_t^T 1_{\{\tau>s\}} v_s e^{-\int_t^s r_u du} ds \middle| \mathcal{G}_t\right] = 1_{\{\tau>t\}}\mathbb{E}^{\mathbb{Q}}\left[\int_t^T v_s e^{-\int_t^s R_u du} ds \middle| \mathcal{F}_t\right], \quad (A.5)$$

$$\mathbb{E}^{\mathbb{Q}}\left[1_{\{t<\tau\le T\}} e^{-\int_t^\tau r_s ds} Z_\tau \middle| \mathcal{G}_t\right] = 1_{\{\tau>t\}}\mathbb{E}^{\mathbb{Q}}\left[\int_t^T Z_\tau \gamma_s e^{-\int_t^s R_u du} ds \middle| \mathcal{F}_t\right]. \quad (A.6)$$

Theorem A.3 allows us to recover the explicit formula for the zero coupon bond with the further assumption of conditional independence between each hazard rate component and the short rate and with the assumption that the payment in case of default will happen at maturity. As for this last assumption, what is important is for the payment to happen at a deterministic known time, that we assume to coincide with the maturity for simplicity. This assumption allows for explicit formulas, making the model more tractable in the case of default, since formula A.6. cannot otherwise be solved analytically. The drawback to such assumption is a small loss in realism, as the reimbursement time is not always set to be equal to maturity.

Corollary A.3.1. *Under the assumptions in Section 3.2, the zero coupon bond pricing formula is:*

$$P_R(0,T) = P_{RF}(0,T)\prod_{i=0,4,5} e^{A_i(0,T)-C_i(0,T)\gamma_{i,0}}\prod_{i=1,2,3,6} e^{H_i(0,T)-M_i(0,T)\gamma_{i,0}} + \delta P_{RF}\left(1-\prod_{i=0,4,5} e^{A_i(0,T)-C_i(0,T)\gamma_{i,0}}\prod_{i=1,2,3,6} e^{H_i(0,t)-M_i(0,T)\gamma_{i,0}}\right),$$

where A_i, C_i, H_i and M_i are:

$$C_i(0,T) = \frac{2(\exp\{Td_i\}-1)}{2d_i+(k_i+d_i)(\exp\{Td_i\}-1)},$$
$$A_i(0,T) = \frac{2k_i\theta_i}{\sigma_i^2}\log\left\{\frac{2d_i\exp\{(k_i+d_i)T/2\}}{2d_i+(k_i+d_i)(\exp\{Td_i\}-1)}\right\},$$
$$d_i = \sqrt{k_i^2+2\sigma_i^2}$$
$$M_i(0,T) = \frac{1}{k_i}\left(1-e^{-k_iT}\right)$$
$$H_i(0,T) = \int_0^T \lambda_i\left(\frac{\eta_i}{\eta_i+\frac{1}{k_i}(1-e^{-k_i(T-S)})}-1\right)ds.$$

Proof. Under the complete filtration $\mathcal{G}_t$ and fixing $t = 0$, the price of the zero coupon bond is expressed as:

$$P_R(0,T) = \mathbb{E}^{\mathbb{Q}}\left[1_{\{\tau>T\}}e^{-\int_0^T r_u du}\middle|\mathcal{G}_0\right] + \delta\mathbb{E}^{\mathbb{Q}}\left[1_{\{0<\tau\le T\}}e^{-\int_0^T r_u du}\middle|\mathcal{G}_0\right].$$

By Theorem A.3, we have that

$$\begin{aligned}\mathbb{E}^{\mathbb{Q}}\left[1_{\{\tau>T\}}e^{-\int_0^T r_u du}\middle|\mathcal{G}_0\right] &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T (r_u+\gamma_u)du}\middle|\mathcal{F}_0\right]\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right]\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right]\\ &= P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right],\end{aligned}$$

where in the last step we have used the assumption of conditional independence between the hazard rate components and the risk-free short rate.

By Lemma A.2, we have that

$$\begin{aligned}\mathbb{E}^{\mathbb{Q}}\left[1_{\{0<\tau\le T\}}e^{-\int_0^T r_u du}\middle|\mathcal{G}_0\right] &= \frac{\mathbb{E}^{\mathbb{Q}}\left[1_{\{\tau<T\}}e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right]}{\mathbb{P}(\tau>0|\mathcal{F}_0)}\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\mathbb{E}^{\mathbb{Q}}\left[(1-1_{\{\tau>T\}})\middle|\mathcal{F}_T\right]\middle|\mathcal{F}_0\right]\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right] - \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\mathbb{E}^{\mathbb{Q}}\left[(1_{\{\tau>T\}})\middle|\mathcal{F}_T\right]\middle|\mathcal{F}_0\right]\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right] - \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\mathbb{Q}(\tau>T|\mathcal{F}_T)\middle|\mathcal{F}_0\right]\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right] - \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right]\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right] - \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right]\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right]\\ &= \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T r_u du}\middle|\mathcal{F}_0\right]\left(1-\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right]\right)\\ &= P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}\left[1-e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right],\end{aligned}$$

where in the last step we have again used the assumption of conditional independence between the risk-free short rate and the hazard rate components. Then, we find that

$$\begin{aligned}P_R(0,T) &= P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right] + \delta P_{RF}(0,T)\mathbb{E}^{\mathbb{Q}}\left[1-e^{-\int_0^T \gamma_u du}\middle|\mathcal{F}_0\right]\\ &= P_{RF}(0,T)\prod_{i=0,4,5}\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_{i,u}du}\middle|\mathcal{F}_0\right]\prod_{i=1,2,3,6}\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_{i,u}du}\middle|\mathcal{F}_0\right]\\ &\quad + \delta P_{RF}\left(1-\prod_{i=0,4,5}\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_{i,u}du}\middle|\mathcal{F}_0\right]\prod_{i=1,2,3,6}\mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^T \gamma_{i,u}du}\middle|\mathcal{F}_0\right]\right)\\ &= P_{RF}(0,T)\prod_{i=0,4,5} e^{A_i(0,T)-C_i(0,T)\gamma_{i,t}}\prod_{i=1,2,3,6} e^{H_i(0,T)-M_i(0,T)\gamma_{i,T}}\\ &\quad + \delta P_{RF}\left(1-\prod_{i=0,4,5} e^{A_i(0,T)-C_i(0,T)\gamma_{i,T}}\prod_{i=1,2,3,6} e^{H_i(0,T)-M_i(0,T)\gamma_{i,T}}\right),\end{aligned}$$

where the functions $A(0,T)$ and $C(0,T)$, as defined in Section 3.2, are the well-known results for the C.I.R. model. Their proof can be found in the original paper, Cox et al. (2005).

$$C_i(0,T) = \frac{2(\exp\{Td_i\}-1)}{2d_i+(\beta_ik_i+d_i)(\exp\{Td_i\}-1)},$$
$$A_i(0,T) = \frac{2\beta_ik_i\theta_i}{(\beta_i\sigma_i)^2}\log\left\{\frac{2d_i\exp\{(\beta_ik_i+d_i)T/2\}}{2d_i+(\beta_ik_i+d_i)(\exp\{Td_i\}-1)}\right\}.$$

For what concerns the functions $M_i(0,T)$ and $H_i(0,T)$, we follow the proof in Rocha-Arteaga and Sato (2001). Let us consider $\gamma_{i,t} = \gamma_{i,t_0}e^{-k_i(t-t_0)} + \int_{t_0}^t e^{-k_i(t-u)}dL_{i,u}^{\mathbb{Q}}$. For the sake of legibility, from here onward the index i will be dropped. Therefore, we have $\gamma_t = \gamma_{t_0}e^{-k(t-t_0)} + \int_{t_0}^t e^{-k(t-u)}dL_u$, with

$$\begin{aligned}\int_{t_0}^t \gamma_u du &= \int_{t_0}^t\left(\gamma_{t_0}e^{-k(u-t_0)}+\int_{t_0}^u e^{-k(u-s)}dL_s\right)du\\ &= \gamma_{t_0}\frac{1}{k}\left(1-e^{-k(t-t_0)}\right)+\int_{t_0}^t\int_{t_0}^t 1_{s<u}e^{-k(u-s)}dL_s du\end{aligned}$$

Table B.53
Welch's t-test results.

Issuer	Month	Statistic	PValue	DoF
AEROPORTI DI ROMA SPA	1	−0.15731	0.56207	36.79406
	2	0.16216	0.43612	30.61713
	3	6.61117	0.00000	29.00015
	4	−4.41889	0.99994	29.03874
	5	−2.76923	0.99526	30.47511
	6	−3.51146	0.99939	35.93342
	7	0.82067	0.20889	32.65200
	8	3.28230	0.00122	32.93213
	9	3.75948	0.00036	30.23332
	10	1.73584	0.04633	30.59556
ALPERIA SPA	1	1.59828	0.06026	29.82415
	2	0.09402	0.46271	57.07440
	3	6.62382	0.00000	29.00000
	4	−0.53001	0.70078	50.25944
	5	1.00000	0.16279	29.00000
	6	4.67945	0.00003	29.00000
	7	0.81723	0.20873	52.91374
	8	0.24111	0.40521	52.32273
	9	4.47833	0.00004	35.04297
	10	4.96042	0.00001	30.00000
ASSICURAZIONI GENERALI SPA	1	0.11118	0.45593	57.71530
	2	0.82901	0.20525	57.99080
	3	6.81217	0.00000	29.22319
	4	0.77871	0.21967	57.62312
	5	0.20635	0.41862	57.94698
	6	2.47066	0.00828	56.00512
	7	0.53660	0.29680	57.99735
	8	0.24148	0.40502	57.79071
	9	0.18517	0.42691	51.69553
	10	1.76066	0.04171	59.72568
BANCO BPM SPA	1	−4.36618	0.99997	57.00076
	2	2.20281	0.01719	34.50706
	3	8.47518	0.00000	29.01043
	4	3.58427	0.00061	29.01435
	5	8.21124	0.00000	29.01359
	6	4.72285	0.00003	29.00683
	7	−0.46549	0.67831	56.20276
	8	−0.01883	0.50748	57.98938
	9	0.19639	0.42250	57.99426
	10	0.10407	0.45873	59.88951
COMMERZBANK AG	1	0.23521	0.40744	57.97731
	2	6.50393	0.00000	31.63000
	3	3.16831	0.00171	31.33331
	4	−0.33737	0.63147	57.79492
	5	−0.27274	0.60699	57.94408
	6	−0.46383	0.67774	57.72970
	7	0.02469	0.49019	57.99051
	8	−0.04079	0.51620	57.99293
	9	−0.00188	0.50075	89.99836
EUROGRID GMBH	1	−1.93814	0.97059	45.50655
	2	−0.70471	0.75760	42.87212
	3	−2.76932	0.99623	57.94931
	4	0.70987	0.24036	56.17673
	5	2.56408	0.00652	56.44572
	6	2.31420	0.01240	50.15193
	7	−0.87300	0.80679	55.66046
	8	−1.63911	0.94628	50.29588
	9	−3.05946	0.99820	48.96166
	10	1.33517	0.09531	34.28121
EUSOLAG EUROPEAN SOLAR AG	1	2.27942	0.01509	29.02335
	2	−1.91914	0.96789	30.96566
	3	−0.28503	0.61155	45.86868
	4	−2.45094	0.99116	51.49948
	5	−0.32407	0.62625	41.70064
	6	−2.87782	0.99703	48.59227
	7	−2.07430	0.97950	87.49364

(*continued on next page*)

$$= \gamma_{t_0} \frac{1}{k}\left(1 - e^{-k(t-t_0)}\right) + \int_{t_0}^{t} \left(\int_{s}^{t} e^{-k(u-s)} du \right) d L_s$$

Table B.53 (*continued*).

Issuer	Month	Statistic	PValue	DoF
LANDESBANK BADEN WUERTTEMBERG	1	4.35685	0.00007	29.45998
	2	12.95402	0.00000	29.32287
	3	18.69593	0.00000	29.08982
	4	39.66474	0.00000	29.52654
	5	2.97179	0.00289	30.07803
	6	7.94306	0.00000	31.90715
	7	8.06909	0.00000	30.55526
	8	1.70054	0.04673	70.16365
MUENCHENER HYPOTHEKENBANK EG	1	4.53421	0.00001	57.99748
	2	5.78660	0.00000	29.00610
	3	6.82411	0.00000	29.04634
	4	30.79751	0.00000	29.08093
	5	31.43855	0.00000	29.01482
	6	27.74198	0.00000	29.00912
	7	4.21712	0.00011	29.31489
	8	14.70451	0.00000	29.11135
	9	5.58106	0.00000	29.03274
	10	8.93493	0.00000	52.50235
RWE AG	1	1.76444	0.04171	53.07122
	2	1.74998	0.04501	30.98527
	3	−0.58063	0.71722	32.04586
	4	1.66470	0.05100	51.89174
	5	0.88624	0.18972	53.83822
	6	−0.06577	0.52609	51.61692
	7	0.26219	0.39726	39.99043
	8	−0.10625	0.54206	43.04607
	9	2.07910	0.02137	50.23360
	10	1.29240	0.10286	31.17359
BPCE SA	1	5.08823	0.00001	29.03135
	2	10.13030	0.00000	29.00575
	3	17.81147	0.00000	29.01806
	4	7.91860	0.00000	29.00365
	5	8.21844	0.00000	29.00662
	6	3.16479	0.00181	29.03965
	7	0.22773	0.41069	30.46391
	8	−1.33976	0.90566	36.15265
	9	4.65269	0.00001	53.12161
ILE-DE-FRANCE MOBILITES	1	2.58521	0.00727	31.67719
	2	0.57494	0.28476	30.71333
	3	−1.16425	0.87406	36.48214
	4	−0.80259	0.78711	53.33585
	5	−4.53043	0.99998	50.25542
	6	1.88205	0.03494	29.06142
	7	0.76059	0.22598	35.26328
	8	1.05683	0.14965	29.04933
	9	−1.47723	0.92714	51.39864
	10	1.26149	0.10674	46.03101
VINCI SA	1	−2.79773	0.99633	48.96502
	2	−0.56497	0.71282	55.80685
	3	−0.39951	0.65449	56.58949
	4	−0.15665	0.56196	57.23850
	5	−1.54998	0.93626	49.73382
	6	−12.39114	1.00000	44.59572
	7	−4.51582	0.99998	56.44672
	8	−4.92522	1.00000	57.05412
	9	−5.00995	1.00000	55.88071
	10	−3.79845	0.99982	57.80518

(*continued on next page*)

$$= \gamma_{t_0} \frac{1}{k}\left(1 - e^{-k(t-t_0)}\right) + \int_{t_0}^{t} \left[\frac{1}{k}\left(1 - e^{-k(t-s)}\right) \right] d L_s.$$

Now, let us define $g(s) = \frac{1}{k}\left(1 - e^{-k(t-s)}\right)$. Then, we have $\int_{t_0}^{t} \gamma_u du = \gamma_{t_0} \frac{1}{k}\left(1 - e^{-k(t-t_0)}\right) + \int_{t_0}^{t} g(s) d L_s$. Let us compute the characteristic function of the process $\int_{t_0}^{t} \gamma_u du$ given the filtration $\mathcal{F}_{t_0}$:

$$\mathbb{E}\left[e^{i\xi \int_{t_0}^{t} \gamma_u du} \middle| \mathcal{F}_{t_0} \right] = e^{\frac{i\xi \gamma_{t_0}}{k}\left(1 - e^{-k(t-t_0)}\right)} \mathbb{E}\left[e^{i\xi \int_{t_0}^{t} g(s) d L_s} \right],$$

Table B.53 (*continued*).

Issuer	Month	Statistic	PValue	DoF
LA BANQUE POSTALE HOME LOAN SFH SA	1	53.10268	0.00000	29.00027
	2	24.75411	0.00000	29.00000
	3	17.04963	0.00000	29.00000
	4	14.21761	0.00000	29.00000
	5	11.90103	0.00000	29.00000
	6	15.58685	0.00000	29.00000
	7	10.11652	0.00000	29.00000
FAURECIA SE	1	−0.38388	0.64874	56.32783
	2	−0.15087	0.55970	57.91121
	3	−0.03079	0.51223	57.99562
	4	−0.06130	0.52433	57.99979
	5	0.01265	0.49498	57.99986
	6	−0.05378	0.52135	57.99158
	7	−0.02313	0.50919	57.99958
	8	−0.00091	0.50036	57.99997
	9	0.00812	0.49677	58.00000
	10	0.56536	0.28697	59.86707
SCHNEIDER ELECTRIC SE	1	0.06276	0.47509	54.61162
	2	1.94484	0.03018	32.96106
	3	−0.73730	0.76759	44.31788
	4	−2.73280	0.99581	56.13154
	5	−6.65949	1.00000	57.50639
	6	−0.34541	0.63392	30.39050
	7	−25.11335	1.00000	43.02781
	8	−26.24362	1.00000	45.53011
	9	−5.88071	1.00000	57.74033
	10	−21.52485	1.00000	57.28777
CAISSE NATIONALE DE REASSURANCE MUTUELLE AGR GROUPAMA	1	1.82956	0.03674	48.45575
	2	5.98790	0.00000	30.96525
	3	15.03267	0.00000	31.86677
	4	9.18055	0.00000	35.42333
	5	1.23747	0.11046	57.80759
	6	3.16881	0.00136	46.23825
	7	0.39205	0.34823	57.99775
	8	0.12847	0.44911	57.98870
	9	0.58225	0.28133	57.92448
	10	4.93170	0.00001	31.64718
ORPEA SA	1	23.43636	0.00000	29.17936
	2	5.04954	0.00000	51.28106
	3	−0.40974	0.65825	57.98959
	4	−0.03457	0.51373	57.99500
	5	−0.06382	0.52533	57.96325
	6	0.00663	0.49737	57.99974
	7	−0.00607	0.50241	57.99949
	8	−0.01191	0.50474	69.99915
ALD SA	1	−0.16467	0.56511	57.98953
	2	−0.14301	0.55661	57.90779
	3	0.03492	0.48613	57.99901
	4	3.19018	0.00170	29.01364
	5	1.78098	0.04270	29.00000
	6	0.99874	0.16114	55.31066
	7	0.42076	0.33774	57.87984
	8	−2.83604	0.99711	80.13258
NERVAL SAS	1	0.97916	0.16657	41.77972
	2	−0.22454	0.58835	47.15845
	3	2.10444	0.02204	29.13497
	4	1.66539	0.05250	34.08821
	5	2.12031	0.01992	42.60242
	6	0.20878	0.41773	50.93043
	7	1.36844	0.08795	64.77942

$$\mathbb{E}\left[\exp\left\{i\xi\int_{t_0}^{t} g(s)dL_s\right\}\right] = \mathbb{E}\left[\lim_{n\to+\infty}\exp\left\{i\xi\sum_{j=1}^{n} g(s_{j-1})(L_{s_j}-L_{s_{j-1}})\right\}\right]$$
$$= \lim_{n\to+\infty}\prod_{j=1}^{n}\mathbb{E}\left[\exp\left\{i\xi g(s_{j-1})(L_{s_j}-L_{s_{j-1}})\right\}\right]$$
$$= \lim_{n\to+\infty}\prod_{j=1}^{n}\exp\left\{\psi(\xi g(s_{j-1}))(s_j-s_{j-1})\right\}$$
$$= \exp\left\{\lim_{n\to+\infty}\sum_{j=1}^{n}\psi(\xi g(s_j))(s_j-s_{j-1})\right\}$$
$$= \exp\left\{\int_{t_0}^{t}\psi(\xi g(s))ds\right\},$$

where ψ is the characteristic exponent of the Lévy process L_s. The switch between the integral end limit operators is possible since the function $g(s)$ is bounded and continuously differentiable, then the Lebesgue Dominated Convergence Theorem can be applied. Therefore, the pricing formula can be obtained just by setting $\xi = -i$. Recalling that $L_s = \sum_{n=1}^{N_s} J_n$ is a Compound Poisson process with i.i.d. exponential jumps J_n, $J_n \sim \exp(\eta)$, having characteristic function

$$\varphi(\xi) = \exp\left\{s\lambda\left(\frac{\eta}{\eta - i\xi} - 1\right)\right\},$$

and by setting $\xi = -ig(s)$, we obtain the expression for $H(t_0, t)$. Finally, we set $t_0 = 0$ and $t = T$ and get the solutions for A_i, C_i, H_i and M_i defined in Eq. (8) and (10):

$$M_i(0,T) = \frac{\beta_i}{k_i}\left(1 - e^{-k_i T}\right)$$
$$H_i(0,T) = \int_0^T \lambda_i\left(\frac{\eta_i}{\eta_i + \frac{\beta_i}{k_i}(1 - e^{-k_i(T-s)})} - 1\right)ds. \quad \square$$

A.1. Ranking corporations via climate index

By the definition of the stochastic hazard rate in Eq. (5) we have that:

$$\gamma_t = \gamma_{0,t} + \sum_{i=4,5}\beta_i\gamma_{i,t} + \sum_{i=1,2,3,6}\beta_i\gamma_{i,t}.$$

Then, by taking the conditional expectation we have

$$\mathbb{E}_0[\gamma_T] = \mathbb{E}_0[\gamma_{0,T}] + \sum_{i=4,5}\beta_i\mathbb{E}_0[\gamma_{i,T}] + \sum_{i=1,2,3,6}\beta_i\mathbb{E}_0[\gamma_{i,T}]$$
$$= \gamma_{0,0}e^{-k_0T} + \theta_0(1-e^{-k_0T}) + \sum_{i=4,5}\beta_i\left(\gamma_{i,0}e^{-k_iT} + \theta_i(1-e^{-k_iT})\right)$$
$$+ \sum_{i=1,2,3,6}\beta_i\left(\gamma_{i,0}e^{-k_iT} + \lambda_i\frac{1}{\eta_i}\int_0^T e^{-k_i(T-s)}ds\right)$$
$$= \gamma_{0,0}e^{-k_0T} + \theta_0(1-e^{-k_0T}) + \sum_{i=4,5}\beta_i\left(\gamma_{i,0}e^{-k_iT} + \theta_i(1-e^{-k_iT})\right)$$
$$+ \sum_{i=1,2,3,6}\beta_i\left[\gamma_{i,0}e^{-k_iT} + \lambda_i\frac{1}{k_i\eta_i}\left(1-e^{-k_iT}\right)\right]$$

and by letting $T \to +\infty$ we get

$$\lim_{T\to+\infty}\mathbb{E}_0[\gamma_T] = \theta_0 + \sum_{i=4,5}\beta_i\theta_i + \sum_{i=1,2,3,6}\beta_i\frac{\lambda_i}{k_i\eta_i}.$$

where each component of the summation gives the long-run mean impact of the ith factor on the hazard rate.

Appendix B. Tables of the results

This Appendix holds the details of the ARIMAX model results of the issuers identified in Section 4.1, summarized in Tables B.9–B.52. Additionally, Table B.53 shows the results of the robustness tests detailed in Section 4.2.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108664.

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