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Understanding climate risk in Europe: Are transition and physical risk priced in equity and fixed-income markets?

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ABSTRACT

This study explores how climate-related risk factors influence the European equity and fixed-income markets. We examine the effect of specific physical risk drivers, including temperature fluctuations, drought, floods, wind, and wildfire risk, on both stocks and bonds. Additionally, we assess the impact of transition risk using two potential indicators: the log-returns of futures on European Carbon Allowances and a Transition Risk Index derived from credit default spreads. We also compare them to see if they carry the same information. Our findings reveal that climate risk variables have different effects on stocks and bonds, with stock returns appearing mostly unaffected by climate-related variables. In contrast, bond z-spreads show significant statistical relationships with both physical and transition climate risks. Physical risk, on average, rewards the green bonds in the sample, and penalizes the traditional bonds. As for transition risk, the two proxies are shown to capture different types of information and to affect different bonds. This suggests that credit default swaps are pricing a transition risk that goes beyond carbon emissions.

1. Introduction

In this study, we seek to determine how climate risk affects the European equity market, focusing on utilities, and the bond market, for both green and non-green bonds. Given the European Union's goal of a green transition, it has become increasingly important for global investors, and EU firms, to identify reliable indicators for the assessment of climate risk. The challenge with climate risk, however, is its complex and multifaceted nature, which makes it difficult to identify its specific drivers. Climate risk encompasses two main components: transition risk and physical risk. Transition risk refers to the uncertainty arising from regulatory changes that restrict or ban certain technologies, potentially impacting corporate profitability and their capacity to repay debts. It also includes the increased costs linked to technological changes and to the need to adapt to newer, greener consumer preferences. These changes can lead to significant alterations in the business environment, requiring firms to adapt quickly or face the financial consequences of their inaction. Physical risk, on the other hand, involves the potential for financial losses due to extreme weather events, the frequency of which is increasing because of climate change, and due to gradual changes in local climate. These alterations can have a direct impact on infrastructure, production, and overall business operations, leading to increased costs and reduced profitability.

Although these definitions might seem clear from a theoretical perspective, they do not point to specific economic variables that can be measured to assess risk. To address these challenges, our study aims to test various potential climate risk drivers to understand their impact on the market. Our hypothesis is that corporate bond spreads and utility stock prices already incorporate climate risk

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into pricing, and we seek to identify the specific factors which contribute to this. To achieve this, we propose an econometric analysis of European utility stock prices and of the European bond market. Due to its elusive nature, special attention is paid to transition risk. We examine the statistical significance of two potential proxies: the log-returns of futures on the carbon allowances (ECF) of the European Emissions Trading Scheme and the transition risk index developed by Blasberg et al. (2021), computed on 20-year tenor CDS. As for physical risk, we explore the impact of various environmental factors, including temperature, floods, droughts, wind speed, and an index of wildfire risk. Through this comprehensive analysis, we aim to provide readers with a clearer understanding of how climate risks influence the prices of utility stocks and the European bond market. This will hopefully help regulators understand the impact of climate risk on bonds and equities, and investors make more informed decisions when navigating a financial landscape increasingly shaped by climate change and regulatory shifts toward sustainability.

The remainder of the paper is structured as follows: Section 2 details the extant literature and the contributions made in this work; Section 3 introduces the time series models for the analysis of stocks and bonds; Section 4 details the nature and the sources of the data used; Section 5 presents the results of the analysis and Section 6 concludes.

2. Literature review

In the existing literature, several studies have explored spillover effects between carbon prices and stock markets. In Chen et al. (2024), the authors find evidence that the growth in country-level CO_2 emissions is a priced risk factor that captures the cross section of stock portfolio returns. Garcia-Jorcano et al. (2022) use CO_2 emission allowance returns as a proxy for changes in climate risk and find that financial markets price carbon risks asymmetrically. They find asymmetric tail dependence indicating that the risk exposure of industry returns depends on the climate risk scenario and on whether downside risk or upside risk prevails in the market. Moreover, they find that downside risk is exacerbated when changes in CO2 emission allowance prices indicate a favorable (green) climate scenario, whereas the opposite is true when they indicate an adverse (brown) one. Furthermore, Hanif et al. (2021) study the dependence structure, via copula functions, between six renewable energy indices and European Emissions Trading Scheme carbon allowance daily prices, from May 18, 2011, to March 05, 2020. The copula results show that the European emission allowance prices are predominantly symmetrically related, i.e., in the center and in the tails, with the clean energy indices that they considered. Dutta et al. (2018) study the link between the carbon emission market and the market of clean energy stocks by employing the bivariate VAR-GARCH approach, finding that the European Emissions Trading Scheme carbon allowance prices affect the renewable energy stock returns positively, although the association is usually found to be statistically insignificant. Importantly, this finding holds for both the US and European markets. Hsu et al. (2023) find the presence of a pollution premium that could not be explained by existing systematic risks, investor preferences, market sentiment, political connections, or corporate governance; they find that firms with more toxic emissions are associated with higher current profitability, and more environmental litigation; high-emission firms' future profitability is lower after governments impose stricter environmental regulations; moreover, high-emission firms observe a favorable shock in response to Donald Trump's 2016 U.S. presidential election win, which suggests a connection between emission-related return predictability and changes in environmental policies. Azar et al. (2021) find that higher ownership by the Big Three (BlackRock, Vanguard, and State Street Global Advisors) is followed by lower carbon emissions. Blasberg et al. (2021) propose a transition risk measure based on the difference between the median CDS spreads of green and brown firms, which increases when policy events trigger a rise in carbon risk, and decreases when the market expects a loosening of the regulatory framework.

What emerges from this review is the absence of a clear consensus on an indicator for transition risk, and of a comparison between multiple potential proxies. With our analysis we aim to fill this gap, and compare the indicator that is most frequently encountered in the literature, the log-returns of European Emissions Trading Scheme carbon allowances, with the promising Transition Risk Index proposed by Blasberg et al. (2021). The goal is to discover which of the two has the greater significance, and whether they carry the same information.

Concerning the impact of physical risk on the stock market, Constanze et al. (2024) find that the European stock market reacts to climate science information provided by the Intergovernmental Panel on Climate Change (IPCC). They uncover that stock prices display statistically significant reactions to each of the IPCC's sub-reports, with the direction of the movement varying depending on the sector. Additionally, it emerges that sectors that are more exposed to climate risk exhibit the strongest response, while the alternative energy sector, a low-emission industry, consistently receives positive stock price reactions, suggesting its hedging potential against climate risk. They also find that sector-level exposure is a stronger determinant of such reaction than corporate emissions responsibility. Furthermore, Yan et al. (2022) find that a sustained rise in temperature has a negative impact on listed companies, which in turn can lead to significantly lower stock returns. Moreover, they find that larger listed companies have more resources available to them than smaller ones and are able to deploy resources in a timely manner in response to market movements, which gives them greater resilience to risk. Therefore, the negative impact of a sustained rise in temperature on larger listed companies is significantly lower than on smaller listed companies. Griffin et al. (2019) uncover that the equity prices of companies operating in regions where Extreme Heat and Storm events occur tend to fall by an average of 0.42 percent in the following month. This impact is more pronounced for smaller firms, with their equity prices dropping by 1.08 percent on average, likely because their operations are less geographically diverse, which makes them more vulnerable. The reduction in equity prices also correlates with the severity of the events, and this effect has become more significant in the past decade. Pagnottoni et al. (2022) observe different stock market reactions to natural hazards depending on the country where the events took place. They find that the stock market indices they examine are especially sensitive to disturbances in European countries, which generally have a negative impact on market performance. Additionally, the study highlights significant spillover effects between market indices and natural disasters from different regions, indicating that shocks in one area can influence stock markets in other areas. For what concerns physical risk, our work aims to expand on the results concerning the role of firm size in quantifying exposure, by investigating whether the impact of physical variables depends on firm sector, or on its country. Moreover, we make use of a larger number of physical risk indicators than previously seen in the literature, and they are selected in line with regulatory requirements. Their observations come from satellite data, which is available in long time series and at a daily frequency.

In the case of fixed-income instruments, several studies explore various aspects of physical risk. Allman (2021) finds that the U.S. market incorporates into pricing a specific physical risk metric: the Sea Level Rise (SLR) index. The research shows that corporate bonds from companies with higher SLR risk carry a climate risk premium at issuance, with a larger premium observed for firms with geographical concentration. Our research addresses a variety of physical risk indicators, selecting them based on existing academic studies, the European Banking Authority (EBA) Climate Stress Tests and Exercises, and the United Nations Environment Programme Finance Initiative's Climate Risk Landscape reports. We prioritize variables with data granularity, favoring those with higher frequency information. In their work, Bats et al. (2023) examine the influence of climate risk premia in corporate bond markets within the Euro area. To assess climate risk, they employ text-based indices derived from news articles, capturing references to various climate-related events and risks. Their findings suggest that corporate bonds with longer-term maturities are significantly impacted by physical climate risk, indicating a clear risk premium associated with climate concerns. While climate risk premia are also observable in bonds with shorter-term maturities, the effect is less pronounced, and they are smaller and less statistically significant. Our work contributes to the literature by including multiple physical risk factors, and of different types than previously seen in the literature. Additionally, both acute and chronic physical risk are accounted for, simultaneously, through a number of climate proxies. They are based on observable weather variables and selected in line with regulatory guidelines by supranational and international entities.

As for transition risk in the fixed-income market, Antoniuk and Leirvik (2021) study the impact of unexpected political events on the risk and returns of green bonds and on their correlation with other assets. They find that green bonds are exposed to transition risk-related news. In fact, events related to climate change policy are found to impact green bonds indices. They benefited from the 2015 Paris Agreement on climate change and were impacted negatively by the 2016 US Presidential Election. Additionally, in Tesfaye et al. (2021) the authors uncover that firms that are more committed to climate change action tend to issue a higher proportion of long-term debt. They link this to the reduced default risk and improved credit ratings that these companies face, due to their lower exposure to transition risk. Our work draws on these results, seeking to further evaluate the link between firm debt, as represented by quoted fixed-income instruments of the green and non-green types, and transition risk. We perform a time-series analysis, as opposed to an event study, and include two potential risk proxies, with the additional aim of performing a comparison between the two. Insights are then provided into which transition-risk indicator has the greater explanatory power for debt markets, and on whether they carry the same information.

From the modeling perspective, Agliardi and Agliardi (2021) propose a credit-risk framework for fixed-income instruments that can account for their exposure to climate risk. They consider that balance sheet quantities are impacted by climate policy shocks and extreme weather events. Empirically, Cepni et al. (2022) consider both types of risk, transition and physical, and their impact on – among other assets – green bonds. They use text-based indices and investigate their safe haven properties as hedges against climate uncertainty. They find that green bonds consistently show a positive correlation with both climate risk types, compared to other assets like gold. They therefore have particularly notable benefits, as potential hedges against climate risk. Our research takes a direct approach, by using weather-related variables and climate risk indicators sourced from European data services. These include detailed climate data from the European Drought Observatory and the Copernicus Data Service. By integrating these weather indicators, our work aims to offer a more accurate representation of the risks faced by corporate bonds in the Euro area. This choice allows us to track physical risk in real time, providing a robust framework for assessing the impact of climate-related events on corporate bond markets. Therefore, we aim to contribute to the existing literature by investigating the relationship between physical and transition risk and corporate bond spreads, and whether it is consistent with the results relating to the stock market.

Additionally, we consider both green and non-green bonds. This is done in order to extend the literature about the diversification benefits provided by green bonds which, in Reboredo (2018) and Martiradonna et al. (2023), were shown to be present, in different time periods, with respect to a market index of interest for the sustainable transition: energy commodities. We compare and contrast the exposure of green bonds to climate risk with that of traditional bonds by the same issuer, emphasizing a potential difference in the treatment, on the part of the market, of the two types of assets.

3. The model

3.1. Equity market

The first part of the analysis concerns the link between the equity market and climate risk factors. In order to do so, a model for stock returns is selected, based on the features of the data. Due to the presence of autocorrelation, an autoregressive term of order 1 is included. Additionally, all stocks in the sample display ARCH effects in their volatility. For this reason, GARCH and tEGARCH models for variance are considered. The tEGARCH(1,1) model, proposed by Nelson (1991), is selected, as it is found to better fit the volatility structure and to be more stable during the estimation procedure. This makes it preferable to the original GARCH model, introduced in Engle (1982). Additionally, the model residuals reject the null hypothesis of normality of D'Agostino's K test and display excess kurtosis, as has been frequently documented in the literature on financial time series modeling. For this reason, for every stock s, they are assumed to be i.i.d. t-distributed with v_s degrees of freedom. Thus, at any time t, the returns of stock s, $r_{s,t}$, the natural logarithm of their variance, $\log(h_{s,t})$, and the model residuals, $\epsilon_{s,t}$ are described by the following equations

$$\begin{aligned} r_{s,t} &= \mu_s + \beta_{s,0} r_{s,t-1} + \sum_{k=1}^{9} \beta_{s,k} X_{k,t-1} + \sqrt{h_{s,t}}\epsilon_{s,t} \\ \log(h_{e,t}) &= \omega_s + \psi_s \epsilon_{s,t-1}^2 + \phi_s \log(h_{s,t-1}) \\ \epsilon_{s,t} | \mathcal{F}_{t-1} &\sim t_{v_s}(0, \sigma_{s,t}) \\ \sigma_{s,t} &= \sqrt{\frac{v_s - 2}{v_s} h_{s,t}}, \end{aligned} \tag{1}$$

where $X_{k,t-1}$, $k = 1, \dots, 9$, are external regressors. Among them are two factors which have been treated as explanatory variables of stock returns by the extant literature. The first is the MSCI world index, which captures the global trend of the stock market.[1] The second is the VIX index, which represents investor sentiment about stock market volatility.[2] The remaining seven regressors are proxies of transition and physical climate risk, which are described in detail in Section 3.3.

3.2. Bond market

We also seek to analyze the bond market and its exposure to climate risk factors, for green and non-green bonds. In order to do so, we focus on the z-spreads, which more purely represent the issuer-specific component of credit risk. At any point in time t, until contract maturity t_N, the z-spread s_t of a defaultable bond can be recovered from its yield-to-maturity y_t (YTM) by exploiting the following relationship

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

where y^{RF} is the market risk-free or benchmark yield of a bond with the same contractual features, issued by an entity with no credit risk. The time series of benchmark yields cannot be found on the market, because it would require the presence of traded, risk-free but otherwise identical instruments to every bond in the sample. For this reason, it is reconstructed artificially. The reference risk-free rates, required for discounting, are bootstrapped in Matlab from the EURIBOR Interest Rate Swap (IRS) curve. For the purpose of rate interpolation, the Nelson–Siegel–Svensson (NSS)model is used. It was proposed in Nelson and Siegel (1987) and extended in Svensson (1994) and Dahlquist and Svensson (1996). In it, the term structure of spot continuously compounded rates follows the following expansion:

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

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:

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

The F functions have a clear interpretation in terms of the traditional components of a term structure: $F_0(\tau)$ is the long-term level, $F_1(\tau)$ is the slope, which can be upward (when $b_1 < 0$) or downward (when $b_1 > 0$) and has an exponential decay. $F_2(\tau)$ and $F_3(\tau)$ serve to incorporate changes in the overall curvature of the yield curve, while parameters ζ and κ determine the location of the humps or the troughs, as well as their steepness. The risk-free bonds are then priced at every time t, yielding

$$P_{RF}(t, t_N) = \sum_{i=1}^{N} \frac{cF}{(1 + r^{RF}(t, t_i))^{t_i - t}} + \frac{F}{(1 + r^{RF}(t, t_N))^{t_N - t}}, \tag{2}$$

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, F is the bond face value, and c is its coupon rate. The time series of prices are then used to obtain the corresponding YTMs, y_t^{RF}, through the following minimization procedure

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

which is repeated for each t, $0 \le t \le t_N$, and for every bond.

[1] The MSCI World Index captures large and mid-cap representation across 23 Developed Markets (DM) countries, https://www.msci.com/documents/10199/178e6643-6ae6-47b9-82be-e1fc565ededb.

[2] https://www.cboe.com/tradable_products/vix/

Next, a model is selected for the z-spreads, based on their features. An initial analysis of the spreads highlights their non-stationarity, which is detected in the time series of a majority of them: most fail to reject the null hypothesis of the augmented Dickey–Fuller test (ADF) at the 10%, 5%, and 1% significance levels. The test p-values are obtained through regression surface approximation from MacKinnon (1994), with the lag length for the test chosen to minimize the Akaike information criterion. The first differences $\Delta s_t = s_t - s_{t-1}$ are therefore taken. The ADF test is then repeated on the Δs_t and the difference is taken again, for the bonds that reject the non-stationarity hypothesis.

Afterwards, a preliminary linear regression of the form

$$\Delta s_{b,t} = \beta_{b,0} + \sum_{j=1}^{n} \beta_{b,j} X_{b,j,t-1} + \epsilon_{b,t}, \quad \epsilon_{b,t} \sim N(0, \sigma_b^2),$$

is run for each bond b, in order to analyze the time series of residuals. Autocorrelation, non-normality and heteroscedasticity are detected in majority of the bonds, through the Breusch–Godfrey, Jarque–Bera, and Breusch–Pagan Lagrange Multiplier tests, respectively. In particular, the residuals display excess kurtosis, which is incompatible with the hypothesis of a normal distribution. An appropriate model is therefore selected, to account for the presence or absence, depending on each bond, of such features. The ARIMAX model class is able to account for the non-stationarity and autocorrelation of the time series of spreads. Furthermore, since the residuals are not normally distributed and display heteroskedasticity, to each bth time series of spreads, $\{s_{b,t}\}_{t\in\mathbb{N}}$, we fit ARIMA$(p, d, q)$ models with conditionally Student-t-distributed innovations having GARCH variance. This draws from the financial literature on GARCH-class models with long memory and fat-tail distributions, such as Lv and Shan (2013). Finally, we extend the model to include the $X_{b,k}, k = 1, \ldots, n$ exogenous regressors, lagged of one period in order for them to be known at time t, and evaluate their significance. The resulting model is of the ARIMAX type

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

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

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

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

where L^i is the lag operator of order i, $\theta_{b,0}$ is a constant, $\epsilon_{b,t}$ is the model residual at time t of the bth time series, $h_{b,t}$ is its conditional variance, $\sigma_{b,t}$ is the shape parameter of the corresponding Student-t distribution, and ν_b are its degrees of freedom. The GARCH model is not used for all time series, but only for those that reject the null hypothesis of homoskedasticity of the Breusch–Pagan test.

The exogenous regressors play an essential role in the analysis, as their coefficients lead to conclusions about the significance of the respective variables. These variables correspond to the traditional determinants identified in the extant literature, such as in Longstaff and Schwartz (1995), Collin-Dufresne et al. (2001), and Chen et al. (2007), and to the potential proxies of climate risk presented in Section 3.3. The traditional determinants include bond liquidity, based on the findings in Chen et al. (2007), represented by closing percent quoted bid–ask spread. Furthermore, in line with Arbel et al. (1977), the Return on Equity of a firm is also considered, as more profitable companies are expected to have a lower probability of default. Additionally, the proximity of firms to bankruptcy is expected to be reflected in bond spreads. For this reason, firm leverage is included: defined as the book value of debt divided by total book value of assets, it links a company's capital structure to its default probability. When the leverage ratio approaches one, bankruptcy is near. Based on the results of Collin-Dufresne et al. (2001), changes in business climate are added as potential explanatory variables, and represented by the stock market returns of the bond issuer's country. Business climate can also be viewed from the point of view of market appetite for risk. For this reason, the VIX index is added to the exogenous regressors. It also servers the role of volatility proxy. Following the contingent-claims approach to corporate liabilities in Merton (1974), a debt claim is a short position in a put option. Given that the value of an option rises with volatility, it is expected that credit spreads will also be influenced by it. Additionally, as in Collin-Dufresne et al. (2001), the log-returns of Eurozone corporate bond indices, matched to the rating of each bond, are included along with local government yields, yield curve convexity, and yield curve slope. A relationship between prevailing interest rates and corporate bonds was identified in Longstaff and Schwartz (1995), which found that the correlation between default risk and interest rates significantly impacts bond spreads. Whenever including interest rates, such as local government yield, in the analysis, a maturity must be selected. Among the available options are a fixed maturity for all bonds (selected arbitrarily), or a bond-specific one, matched to its duration or to its maturity. The alternatives are evaluated individually and the duration is chosen, as it displays the greater explanatory power. Since the duration of a bond changes every day, the time series of durations is computed for every bond, throughout its life in the sample period. Then, it is used to find, each day, the government yield of the corresponding maturity. The interpolation scheme used is based on the Nelson–Siegel–Svensson model (NSS hereafter). Concerning the slope and the convexity of the yield curve, we use the coefficients b_1 and b_2 of the NSS interpolation scheme. They impact the slope and the curvature basis functions respectively.

3.3. Climate risk proxies

At the time of writing this paper, there is no clear consensus on which precise time series to use as climate risk proxies, in the guidelines by European regulatory bodies. However, the EBA Climate Stress Tests and Exercises and the Climate Risk Landscape reports by the United Nations Environment Programme Finance Initiative identify the general variables of interest for climate stress testing. We therefore select the risk proxies in this analysis among the available indicators of such variables. For each of them, the granularity of the available time series also influences the choice, and preference is given to the ones available at the higher frequency. Additionally, the EU's current Climate Stress Testing method limits physical risk scenarios to shocks, concentrating solely on acute risks and the financial system's resilience to them. This analysis has a broader scope, and aims to capture – if any – the relationship between the equity and fixed-income markets and continuously-measured climate variables, also incorporating chronic physical risk.

As for physical risk, the 2022 Climate Stress Test by the European Central Bank (2022) identifies drought and flood as important risk drivers. For the purpose of representing them in this study, the Soil Moisture Index Anomaly (SMA) is selected. It measures the deviation from usual soil water content at each time of the year. Values identifying severe dryness (below the *wilting point*) are taken as drought proxies, while those corresponding to the inability of the soil to absorb any more water (above the *field capacity*) are taken as proxies for floods. Next, the 2023 Climate Risk Landscape report by the United Nations Environment Programme Finance Initiative, Carlin et al. (2023) indicates a need to account for the impact of storms, hurricanes and typhoons. For this purpose, the non-seasonal components of average daily wind speed, for both the eastward and the northward directions, are included. Depending on the country, they are also linked to the production of energy from renewable sources. The same report also point to wildfire risk, which in this study we proxy through the Copernicus Fire Weather Index (FWI). It measures how favorable the meteorological conditions are for a wildfire to be triggered. Finally, the important role of chronic physical risk is also acknowledged. One of its key indicators is temperature rises, which has consequences on worker productivity and energy demand. We therefore include the non-seasonal component of average daily temperature among the risk indicators.

Finally, and most importantly for our research question, transition risk needs to be accounted for. It is however a difficult quantity to capture, and we rely on the literature for identifying two potential proxies. They are considered one at a time, in order to avoid the problem of multicollinearity, and their level of significance is compared. The first are the log-returns of futures on EU carbon allowances (ECF) of the European Emissions Trading Scheme are considered. The variation in their market price reflects the cost of reducing emissions and increases with stricter policies. The second proxy is built according to the methodology introduced in Blasberg et al. (2021). It is based on CDS spreads: European corporations are ordered by carbon intensity per unit of revenue. Firms below the first quantile are defined as "green" and their CDS spreads are collected in the set $\mathcal{G}_t^m$. Analogously, firms above the last quantile are defined as "brown" and their CDS spreads are gathered in the set $\mathcal{B}_t^m$. Then, the median cost of default protection of green and brown firms is taken for a CDS maturity of m years. It is found as the median CDS spread level for tenor $m = 20$ at every time t, and is denoted as $G_t^m = \text{Med}(\mathcal{G}_t^m)$, $B_t^m = \text{Med}(\mathcal{B}_t^m)$. The difference between the median CDS spreads of brown and green firms is then found. It represents the differential credit risk exposure of brown versus green firms. In Blasberg et al. (2021), this is called the carbon risk (CR) factor:

$$CR_t^m = B_t^m - G_t^m. \tag{3}$$

This factor mimics the dynamics of a portfolio in which default protection is bought for a representative (median) brown company and sold for a representative (median) green firm. When policy events trigger a rise in carbon risk (e.g. expectation of a tighter future regulatory framework), the demand for protection of more (less) exposed firms increases (decreases), resulting in a widening of the wedge. Conversely, if the market expects a loosening of the regulatory framework, there is a narrowing of the wedge (or possibly even a negative wedge). These changes in perceived exposure to carbon risk are aptly represented by the behavior of the CR, which is therefore considered to be an observable proxy for lenders' perception of carbon risk exposure. It is henceforth referred to as the CDS 20y Transition Risk Index (TRI).

To summarize, a total of six physical risk indices and two transition risk indices are included in the present study. The physical risk indicators are: flood risk, drought risk, the nonseasonal component of average daily eastward wind speed (*Wind E/W*), the nonseasonal component of the average daily northward wind speed (*Wind N/S*), the nonseasonal component of average daily temperature (*Temp.*), and the Fire Weather Index (*FWI*). The two transition risk indices, which are considered one at a time, are the ECF log-returns and the CDS TRI 20y.

4. Data

The equity portion of the paper considers 248 European utility companies (the full list of which is reported in Appendix A.1). Table 1 displays the number of stocks in the sample, by country, highlighting their geographical distribution. The number of firms is especially high in Poland, Germany, France, and Italy.

As for the fixed-income portion, the sample is restricted to firms which have issued at least one green bond. Some of the exogenous regressors required by the model limit the scalability of the project: firm leverage and Return On Equity are manually recovered from financial statements. For this reason, we currently restrict the analysis to French, German, and Italian companies. Together, these three countries account for approximately 52.6%[3] of the GDP of the European Union. Therefore, although the scope of the

[3] https://www.imf.org/en/Publications/WEO/weo-database/2024/October/weo-report?c=132,134,136,&s=NGDPD,&sy=2022&ey=2029&ssm=0&scsm=1&scc=0&ssd=1&ssc=0&sic=0&sort=country&ds=.&br=1

Table 1
Number of stocks in the sample, by country.

Country	Number of stocks
Austria	12
Belgium	5
Bulgaria	1
Denmark	19
Estonia	4
France	28
Germany	58
Italy	23
Luxembourg	1
Malta	1
Netherlands	8
Poland	99
Spain	15
Switzerland	11
United Kingdom	3

Table 2
Number of corporate bonds in the sample, by country.

Country	Number of green bonds	Number of non-green bonds
Germany	409	504
Italy	50	190
France	112	718

analysis is restricted, the results may still provide valuable, albeit tentative, insights into wider European trends. The complete list of corporate issuers can be found in Appendix A.2. They are all the green-bond issuers of the three countries, totaling 42 French, 43 German, and 19 Italian firms. In order to facilitate estimator convergence, only bonds with at least 100 observations are included. The number of green and non-green bonds by those issuers is displayed in Table 2, divided by country. German bonds make up a substantial majority of the sample and, interestingly, the difference between the number of green and non-green bonds is small: the former are 409, while the latter, which are issued by the same firms, are 504. On the other hand, for Italy and France, the number of green bonds in the sample is proportionally much lower, as they are only 50 against 190 non-green bonds, for Italy, and 112 green against 718 non-green, for France. It is worth noting that, in order to remove the impact of exchange rate risk, which is not of interest for this study, we only consider euro-denominated bonds.

For daily bonds, stocks, and energy futures prices (Dutch Natural Gas TTF, Coal and Brent), the window of observation is 04/01/2021 to 27/03/2023. The ECF futures prices correspond to the rolled contracts expiring in December of each year (as they are the most liquid), while Coal, Brent and TTF futures prices correspond to the rolled contracts with monthly maturity. Energy commodity data are quoted at Intercontinental Commodity Exchange ICE and are provided by Refinitiv Datastream. Data on stock prices, CDS spreads, bond bid, ask, and mid prices, bond YTMs, interest rates, government yield curves, the VIX index, Eurozone corporate bond indices, national stock market indices, and EU carbon allowance prices is also taken from Refinitiv Datastream. Balance sheet information is gathered from the AIDA database, for some Italian firms. For others, and for the German and French issuers, it is collected from the individual financial statements of each firm.

As for weather variables, the SMA is provided by the Copernicus European Drought Observatory, the FWI is taken from the Copernicus *Fire danger indicators for Europe from 1970 to 2098 derived from climate projections*, while 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. Figs. 1(a)–1(f) show the plots of each weather variable, averaged daily in the sample period and mapped by country. Only countries covered by the sample of stocks and bonds are included.

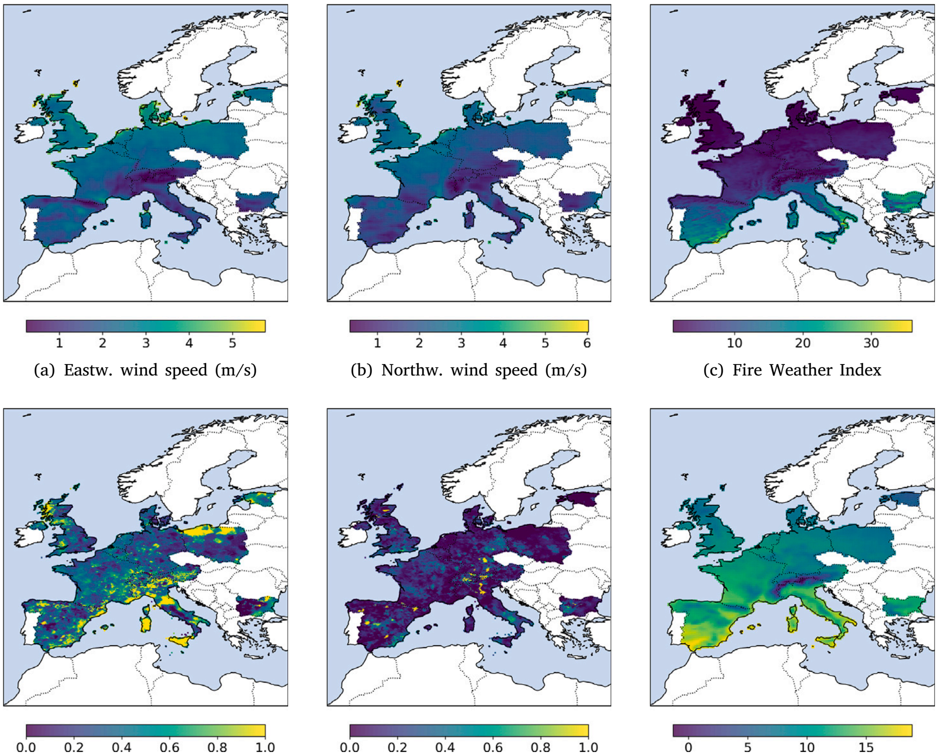
5. Empirical results

5.1. Climate risk in the equity market

The ARX-tEGARCH models are fit to the time series of the stock log-returns. To check the stationarity of the time series we perform the Augmented Dickey–Fuller test, to ensure the convergence of the maximum likelihood estimators. The choice of the Student-t distribution is motivated by the rejection of the null hypothesis of Normality of the D'Agostino's K-squared test.

Tables 16 and 17 provided the estimated coefficient values for stocks for which at least one climate-related variable is statistically significant. Results are presented separately for two model fits: the first takes as transition risk proxy the ECF log-returns, while the second takes the 20-year Transition Risk Index (derived from CDS spreads using Eq. (3)).

Table 16 lists the coefficients of the climate risk variables, when the ECF log-returns are considered for transition risk. Out of a sample of 248 stocks, 28 have a statistically significant coefficient for the ECF log-returns, 28 for the flood index, 12 for temperature,



(a) Eastw. wind speed (m/s) (b) Northw. wind speed (m/s) (c) Fire Weather Index

(d) Drought index (e) Flood index (f) Temperature (°C)

Fig. 1. Average daily values of climate variables by country, over the sample period.

14 for the drought index, 4 for wind (E/W), 4 for wind (N/S), and 5 for the FWI. Table 17, instead, reports the coefficients of the climate risk variables, when the 20-year Transition Risk Index is considered. In this instance, 13 stocks out of the 248 in the sample have a statistically significant coefficient for the Transition Risk Index, 17 for temperature, 31 for the flood index, 12 for the drought index, 1 for wind (E/W), 3 for wind (N/S), and 6 for the Fire Weather Index. Despite the presence of some significant coefficients, although few with respect to the sample size, it is important to note that the regressions yield low R^2 values, indicating that the variables do not explain much of the variability in log returns. This low explanatory power on the part of the regressors aligns with the efficient market hypothesis, as daily stock returns are known to be highly efficient and difficult to predict based on past information. It is also worthy of note, however, that in both Tables 16 and 17, the same physical risk driver emerges as having, by far, the largest number of statistically significant relationships with stock returns: the flood index. It is also the most direct indicator, among the included weather variables, of *acute* physical risk. Acute physical risk arises from extreme weather events, which can cause direct, sudden, and noticeable damages to a firm's revenues. It is therefore not surprising that, if one proxy of climate risk should emerge as having the greater impact on stock returns, it is the one representing floods. We also observe that the impact of this indicator is highly location-dependent: firms directly impacted by floods are expected to exhibit a statistically significant relationship with it. However, this does not imply that firms currently lacking statistically significant relationship with the indicator are immune from flood risk: it only signals that they have not been impacted during the time frame covered by the present work.

Given the low number of statistically significant relationships, even if we aggregate the coefficients by country or by sector, the results do not provide any additional insight. Finally, when observing which issuers are significantly related to both transition risk proxies, we find that, at the 5% significance level, 9 of them are significantly related to both, but mostly with coefficients of opposite sign. However, at the 2.5% (and therefore also at the 1%) significance level, the number of issuers simultaneously related to both is zero.

5.2. Climate risk in the fixed-income market

The ARIMAX(p, d, q) models are fit to the time series of z-spreads. In order to avoid spurious correlations, the exogenous regressors are tested for stationarity. If necessary, their one-period increments are considered. Afterwards, the regressors and the regressands are standardized, because of scale-related issues, and a test of multicollinearity, based on variance inflation factors, is carried out before fitting the models. The order of integration (d) is selected based on the results of the Augmented Dickey Fuller test, with first differences being taken until the null hypothesis of the test is rejected at the 1% significance level. The Auto Regressive and Moving

Average orders (p and q, respectively) are found by selecting the combination that minimizes the Bayes Information criterion of the corresponding ARMAX(p,q) model, fit via maximum likelihood to the spread increments, $(1-L)^d s_{b,t}$. The maximum number of lags is the same that is used in the Breusch–Godfrey test for autocorrelation.

The findings are presented separately for the two transition risk proxies, the ECF log-returns and the CDS TRI 20y. The proportion of statistically significant relationships with climate variables ("S/Total"), as well as their average coefficient ("Avg. Coeff."), per country and per bond type, are summarized in Tables 3 and 4 for the ECF, and 5 and 6 for the TRI 20y.

The first result that emerges concerns physical risk proxies. In all tables, for a number of variables, green bonds and non-green bonds of the same country have opposite average coefficient signs. In Table 3, this holds for flood and drought in Italy, and temperature and northward wind, in Germany. This is also true for flood, northward wind and fire risk in France, as can be seen in Table 4. In Table 5, this holds for the flood, drought, temperature, and northward wind in Italy, and temperature and flood, in Germany. It is also true for northward wind in France, as can be seen in Table 6. Interestingly, in all above cases, except for the French and German flood, the disagreement about the sign of coefficients is such that green bonds have a negative sign, while non-green bonds are positive. Since the dependent variable under study is the z-spread, a negative sign represents a decrease in the perceived riskiness of the bonds, while a positive sign represents an increase. This points to a different treatment on the part of the market of green and non-green bonds, that makes it so that the green bonds in the sample react in a favorable way to increases in climate risk, while non-green ones react negatively. This is interesting in light of the fact that the sample is composed of green and non-green bonds by the same set of issuers.

Multiple factors may contribute to this effect. One relates to issuer and bond features: Fiorillo et al. (2024) find a small negative risk premium for green bonds (the greenium), especially for riskier bonds like unsecured or subordinated issues, and for first-time green issuances. This suggests the market may view these cases as stronger signals of a firm's environmental commitment. Additionally, Goodell et al. (2025) show that climate risk pricing is negatively linked to long-term maturities, in a non-linear way influenced by firm, country, and macroeconomic context. Differences in bond maturities across the sample may help explain a portion of the variations in spread reactions. Additionally, the firm's degree of climate resilience can be an important factor, as it can influence how its spreads react to climate risk. Since each firm's weight in the average coefficients of Tables 3–6 depends on how many bonds it has in the sample, their impact varies. In our dataset, issuers fall into two broad groups: those with a "green" core business (like renewable energy or low-carbon transport) and those with a less clearly green profile (such as banks or energy distributors). The former are more represented among green bonds, potentially explaining lower average climate risk exposure in that group. In contrast, non-green firms dominate the traditional bond sample. Overall, this highlights the value of a potential future analysis of firm-level explanations, delving deeper into the features and business structure of each company in the sample.

The final potential explanation that we bring forth is green-bond specific and is the presence of an investor preference for greenness, as documented in Zerbib (2019) through the uncovering of the "greenium". In light of this, the nature green bonds, with their funds being committed to projects with a positive environmental impact, could make them a more desired asset in the portfolios of investors with green preferences. As a consequence, a greater investor propensity to hold them, as compared to their non-green counterparts, could make their z-spreads less reactive to climate risk. Further extending this line of thinking, manifestations of climate risk could lead to an increase in the demand of green bonds on the part of investors with green preferences, over traditional bonds by the same issuers, in an effort to provide funding towards climate risk mitigation projects. This would drive the reaction of the z-spreads of the same issuer to exhibit opposite signs for green and non-green bonds. This effect can be connected to the Del Giudice et al. (2025), in the case of acute physical risk. They find that green bonds outperform brown bonds after climate-related disasters, with investors adjusting their preferences towards green assets.

We also note that there is a noticeable difference between the countries in the size of this phenomenon, as French and Italian green bonds have a negative average coefficient with many more physical risk proxies than the German. More precisely, in Tables 3 and 4, French and Italian green bond spreads are inversely related to four indices, while German green bonds have a negative relationship with three. As for Tables 5 and 6, French green bond spreads are related to five physical risk indices, the Italian to four, while the German only to two.

The second set of results concerns transition risk, as represented by the two quantities under study: ECF and TRI 20y. Both have a number of statistically significant relationships that is comparable to that of the physical risk variables. Furthermore, the TRI 20y has a consistently larger number of statistically significant relationships than the ECF, except for the case of Italian green bonds. Additionally, and most notably, the average sign of the significant coefficients for the two proxies differs. Table 3 shows that for the ECF, the sign is positive for all Italian and German bonds. In contrast, Table 5, reveals that for the TRI 20y the sign is negative for Italian green bonds as well as for German green and non-green bonds. This suggests that the two proxies may be capturing a different kind of information, namely that the TRI 20y incorporates transition risk components that go beyond carbon risk—or risk directly linked to the price of carbon allowances. To further investigate this hypothesis, we go on to evaluate the dependence between ECF and TRI, in Section 5.3, and also their correlation with energy commodities. Additionally, the two proxies might be related to different sets of bonds in the sample, explaining the change in sign and proportion of statistically significant relationships. We explore this possibility by conducting an in-depth analysis of the significant relationships with the two risk proxies, organizing the results by issuer.

Tables 7, 10, 8, 11, 9, and 12 show the number of statistically significant relationships ("S/Total"), as well as their average coefficient ("Avg. Coeff.") with the two transition risk proxies, at the 1% and 5% significance levels, for all three countries. The results are aggregated by issuer and by bond type (green or non-green), including only issuers which have a number of statistically significant relationships with at least one transition risk proxy strictly greater than 50%. By analyzing these tables, we aim to

Table 3
Number and average coefficient of statistically significant relationships with exogenous regressors, ECF as transition risk proxy ($\alpha = 0.01$).

	Italy				Germany			
	Green bonds		Non-green bonds		Green bonds		Non-green bonds	
	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total
ECF	0.0500	10/50	0.0429	18/190	0.0636	32/409	0.0135	33/504
Temp.	−0.0532	3/50	−0.0313	3/190	−0.0203	24/409	0.0080	27/504
Flood	−0.0433	4/50	0.0021	28/190	0.0078	21/409	0.0498	46/504
Drought	−0.2486	3/50	0.0556	28/190	0.0103	82/409	0.0738	30/504
Wind E/W	−0.0238	11/50	−0.0504	15/190	0.0389	42/409	0.0178	41/504
Wind N/S	0.0026	9/50	0.0018	28/190	−0.0138	23/409	0.0063	36/504
FWI	0.0830	2/50	0.0335	16/190	−0.0221	59/409	−0.0911	75/504

Table 4
Number and average coefficient of statistically significant relationships with exogenous regressors for France, ECF as transition risk proxy ($\alpha = 0.01$).

	France			
	Green bonds		Non-green bonds	
	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total
ECF	0.0550	11/112	−0.0213	47/718
Temp.	−0.0598	4/112	−0.1675	25/718
Flood	0.0090	27/112	−0.0230	131/718
Drought	0.2623	2/112	0.0749	29/718
Wind E/W	−0.0078	3/112	−0.0206	28/718
Wind N/S	−0.0554	4/112	0.0096	47/718
FWI	−0.0544	4/112	0.0207	55/718

Table 5
Number and average coefficient of statistically significant relationships with exogenous regressors, TRI 20y as transition risk proxy ($\alpha = 0.01$).

	Italy				Germany			
	Green bonds		Non-green bonds		Green bonds		Non-green bonds	
	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total
TRI 20y	−0.0802	8/50	0.0264	29/190	−0.0081	49/408	−0.0180	54/504
Temp.	−0.1153	2/50	0.1938	5/190	−0.0170	30/408	0.0317	29/504
Flood	−0.0567	4/50	0.0055	31/190	0.0114	30/408	−0.0441	51/504
Drought	−0.1075	4/50	0.0216	30/190	0.0207	83/408	0.0448	36/504
Wind E/W	0.0083	2/50	0.0528	16/190	0.0299	35/408	0.0206	45/504
Wind N/S	−0.0280	5/50	0.0013	23/190	0.0133	21/408	0.0291	36/504
FWI	0.0653	8/50	0.0234	17/190	−0.0260	54/408	−0.0763	87/504

Table 6
Number and average coefficient of statistically significant relationships with exogenous regressors for France, TRI 20y as transition risk proxy ($\alpha = 0.01$).

	France			
	Green bonds		Non-green bonds	
	Avg. Coeff.	S/Total	Avg. Coeff.	S/Total
TRI 20y	−0.0425	11/112	−0.0218	78/718
Temp.	−0.0386	10/112	−0.0709	28/718
Flood	−0.0170	25/112	−0.0160	102/718
Drought	0.0909	3/112	0.1566	26/718
Wind E/W	−0.0172	4/112	−0.0549	20/718
Wind N/S	−0.0175	4/112	0.0111	49/718
FWI	−0.0407	6/112	−0.0433	56/718

investigate the hypothesis that emerged from the analysis of Tables 3 and 5: namely, that the two proxies might be carrying a different type of information and thus capture statistically significant relationships with different issuers.

In Tables 7–9, it is possible to see that, at the 1% significance level, only one issuer has a statistically significant relationship with both risk proxies for a majority of at least one type of bond: Amprion GmbH. This is true for its green bonds and, interestingly, the sign of the relationship differs. The average coefficient of ECF is positive, while for TRI 20y it is negative. Three other companies show some relationship with both risk proxies, but for a limited proportion of bonds: the "S/Total" ratio is lower than 50%. We therefore observe that the overlap between the significance of the two proxies is very limited – only one issuer – and that, in the one

Table 7
Significant relationships with the transition risk proxies, for Italian issuers (α = 0.01).

			ECF	TRI 20y
ACEA SPA	Green bonds	Avg. Coeff.	0.0234	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	0.0464	0.0362
		S/Total	3/5	1/5
ALERION CLEAN POWER SPA	Green bonds	Avg. Coeff.		−0.3177
		S/Total	0/2	1/2
	Non-green bonds	Avg. Coeff.		
		S/Total	0/1	0/1
ASSICURAZIONI GENERALI SPA	Green bonds	Avg. Coeff.	0.1006	
		S/Total	2/3	0/3
	Non-green bonds	Avg. Coeff.		
		S/Total	0/4	0/4
SNAM SPA	Green bonds	Avg. Coeff.	0.0290	−0.0217
		S/Total	3/5	2/5
	Non-green bonds	Avg. Coeff.	0.0582	
		S/Total	3/11	0/11

Table 8
Significant relationships with the transition risk proxies, for German issuers (α = 0.01).

			ECF	TRI 20y
AAREAL BANK AG	Green bonds	Avg. Coeff.	0.0996	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.		
		S/Total	0/7	0/7
AMPRION GMBH	Green bonds	Avg. Coeff.	0.1005	−0.1726
		S/Total	1/2	1/2
	Non-green bonds	Avg. Coeff.		−0.0438
		S/Total	0/1	1/1
DZ HYP AG	Green bonds	Avg. Coeff.	0.1009	
		S/Total	1/1	0/1
EUSOLAG EUROPEAN SOLAR AG	Green bonds	Avg. Coeff.		0.0566
		S/Total	0/1	1/1
HAMBURGER HOCHBAHN AG	Green bonds	Avg. Coeff.		−0.0149
		S/Total	0/1	1/1
ING DIBA AG	Green bonds	Avg. Coeff.	0.1324	
		S/Total	1/2	0/2
RWE AG	Green bonds	Avg. Coeff.	0.0504	−0.0875
		S/Total	3/5	2/5
	Non-green bonds	Avg. Coeff.		
		S/Total	0/2	0/2

case in which it happens, the coefficients have opposite signs. This result is in line with the hypothesis of the different information carried by the two proxies.

A careful look at Tables 10, 11, and 12 confirms this interpretation, also at the 5% significance level: SNAM S.p.A. green bonds display the same behavior as those by Amprion GmbH. A majority of them has a statistically significant relationship with both risk proxies, at the 5% significance level, but of opposite sign. Once again, as in the case of Amprion GmbH, the average coefficient of ECF is positive, while for TRI 20y it is negative. Importantly, the TRI 20y index reflects the difference between median green and brown CDS spreads. The divergence between the statistically significant relationships of the TRI 20y and the ECF leads us to hypothesize that credit default swaps are currently pricing a transition risk that goes beyond carbon emissions.

Additionally, a geographical distinction emerges between the two transition risk proxies: in both Tables 7 and 10, the most significant proxy for Italy is the ECF, by a wide margin. On the other hand, in Germany, from Tables 8 and 11 what emerges is that the number of firms having a statistically significant relationship with the two indices for at least half of the outstanding green or non-green bonds is almost identical. As for France, the number of firms is the same for the two proxies, at the 1% significance level, but it is much larger for the ECF, at the 5% level, as can be seen in Tables 9 and 12.

Table 9
Significant relationships with the transition risk proxies, for French issuers (α = 0.01).

			ECF	TRI 20y
BANQUE FEDERATIVE DU CREDIT MUTUEL SA	Green bonds	Avg. Coeff.	0.0514	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	−0.0091	−0.0405
		S/Total	3/64	10/64
CREDIT AGRICOLE CORPORATE AND INVESTMENT BANK SA	Green bonds	Avg. Coeff.		−0.0614
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.	0.0401	−0.0447
		S/Total	1/48	2/48
LA BANQUE POSTALE HOME LOAN SFH SA	Green bonds	Avg. Coeff.		−0.1189
		S/Total	0/1	1/1
SCHNEIDER ELECTRIC SE	Green bonds	Avg. Coeff.		−0.0478
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.	0.0412	
		S/Total	1/5	0/5
UNIBAIL-RODAMCO-WESTFIELD SE	Green bonds	Avg. Coeff.	0.0270	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	0.0487	−0.1104
		S/Total	1/33	1/33
VOLTALIA SA	Green bonds	Avg. Coeff.	0.0413	
		S/Total	1/1	0/1

5.3. The informational content of the two transition risk proxies

The empirical analysis highlights a distinction in the role played by the TRI 20y and ECF risk proxies. While both indicators are statistically significant in explaining risk for a number of green bond issuers, the average sign and behavior of their coefficients diverge, suggesting that they capture different dimensions of transition risk. In particular, the TRI 20y – with its direct ties to company's creditworthiness via their CDS – could reflect broader transition-related factors beyond direct exposure to carbon pricing, such as changes in corporate creditworthiness linked to long-term sustainability and adaptation strategies.

This interpretation is supported by the correlation results presented in Table 13, which show no statistically significant association between the TRI index and ECF. Next, we move on to assess the link of the two proxies with the cost of energy—as represented by Dutch TTF, Coal, and Brent futures log-returns. Table 14 shows independence between the TRI and the energy commodity markets (Dutch TTF, Coal, and Brent). Across Kendall's Tau, Spearman's ρ, and Pearson's correlation, the coefficients remain close to zero, and the p-values do not reach standard levels of statistical significance. This suggests that TRI 20y is not responsive to short-term movements in energy markets and does not reflect immediate price-based transition pressures. In contrast, Table 15 reveals statistically significant and positive correlations between ECF and the other energy commodities, particularly TTF. The results from Kendall's Tau and Spearman's ρ indicate robust monotonic relationships, with Pearson's correlation coefficient confirming a significant linear association primarily between ECF and TTF. The correlations between ECF and Coal or Oil are weaker and more variable, with ECF-Coal not statistically significant under Pearson's, and ECF-Oil only weakly so. Therefore, as can be expected, the ECF index is connected to production inputs which lead to carbon emission.

Taken together, these findings suggest that ECF behaves similarly to other traded energy commodities, consistent with its interpretation as a proxy for carbon-related input costs in production. Meanwhile, the TRI 20y index could encapsulate broader, longer-term transition risks embedded in corporate credit profiles. In fact, the TRI 20y is constructed with company CDS having a maturity of 20 years, and therefore reflects longer-term expectations, while the ECF carries information about the emissions produced during the solar year. This temporal misalignment could be responsible for the different informational content of the two proxies. This supports the notion that ECF and TRI provide different perspectives on transition risk, with ECF reflecting immediate market exposures and TRI capturing structural vulnerabilities over a longer horizon.

5.4. Policy implications

In our view, these findings can provide some insight for future policy making. Concerning transition risk, they indicate a need for developing and adopting more comprehensive transition risk metrics, that capture a broader range of risks beyond carbon emissions, to be incorporated into regulatory stress testing and financial reporting requirements. With regard to equity, we observe that the market is currently focused on the impact of acute risk factors, namely floods. This could be an important consideration for the evolving design of climate stress tests. The empirical analysis in this work confirms that these events have a direct impact on firm revenues and are promptly reflected in market prices, while other climate risk factors are almost entirely ignored. As a consequence, given the limited number of statistically significant relationships, the regulator should be aware of a potential underpricing of climate risk in the equity market. In order to evaluate it, at least in the European framework, we suggest to assess the alignment between

Table 10
Significant relationships with the transition risk proxies, for Italian issuers (α = 0.05).

			ECF	TRI 20y
ACEA SPA	Green bonds	Avg. Coeff.	0.0234	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	0.0464	0.0362
		S/Total	3/5	1/5
ALERION CLEAN POWER SPA	Green bonds	Avg. Coeff.		−0.1933
		S/Total	0/2	2/2
	Non-green bonds	Avg. Coeff.		
		S/Total	0/1	0/1
ASSICURAZIONI GENERALI SPA	Green bonds	Avg. Coeff.	0.1006	
		S/Total	2/3	0/3
	Non-green bonds	Avg. Coeff.		0.0595
		S/Total	0/4	1/4
BANCO BPM SPA	Green bonds	Avg. Coeff.	0.0050	−0.0700
		S/Total	3/3	1/3
	Non-green bonds	Avg. Coeff.	0.0263	0.0318
		S/Total	3/24	6/24
FERROVIE DELLO STATO ITALIANE SPA	Green bonds	Avg. Coeff.	0.1862	−0.1464
		S/Total	1/4	2/4
	Non-green bonds	Avg. Coeff.	−0.0778	0.0034
		S/Total	1/10	2/10
INTESA SANPAOLO SPA	Green bonds	Avg. Coeff.	0.0806	0.0460
		S/Total	2/4	1/4
	Non-green bonds	Avg. Coeff.	0.0212	0.0380
		S/Total	10/70	17/70
IREN SPA	Green bonds	Avg. Coeff.	0.0242	−0.0215
		S/Total	2/4	1/4
	Non-green bonds	Avg. Coeff.	0.0257	
		S/Total	1/2	0/2
SNAM SPA	Green bonds	Avg. Coeff.	0.0290	−0.0203
		S/Total	3/5	3/5
	Non-green bonds	Avg. Coeff.	0.0423	−0.0170
		S/Total	5/11	1/11
TERNA RETE ELETTRICA NAZIONALE SPA	Green bonds	Avg. Coeff.	0.0284	
		S/Total	2/4	0/4
	Non-green bonds	Avg. Coeff.	0.0312	−0.0664
		S/Total	1/6	1/6

market sentiment – in terms of stock price reaction to climate risk – and firms' self-reported climate risk exposures under the Corporate Sustainability Reporting Directive (CSRD). Any discrepancies could highlight potential awareness gaps in the perception of risk on the part of the market. In contrast, for the bond market, the results suggest a different policy approach reflecting its longer-term incorporation of climate risk. It can in fact be noted that fixed-income instruments exhibit a sensitivity to climate risk factors that involves a wider array of risk proxies, which are not limited to those with a short-term impact. This could result in a different time-horizon for bonds and equity when performing climate stress-tests, but only after careful consideration of the impact of such different requirements on investor incentives. Finally, when it comes to transition risk, the bond market does show some degree of dependence; however, the nature of this relationship remains unclear. This suggests that the most appropriate proxy for transition risk may differ from those examined in the present study and could require a more general or comprehensive approach.

6. Conclusions

The analysis carried out in this study aims to determine how climate risk affects the European equity market and bond markets, for both green and non-green bonds, testing multiple potential climate risk drivers. The ultimate goal is to provide a better understanding of this type of risk, hopefully helping regulators and investors make more informed decisions, in a financial landscape increasingly shaped by climate change and growing sustainability needs. The working hypothesis in this article is that corporate bond spreads and utilities stock prices already incorporate climate risk into pricing and, in order to test it, an econometric analysis of two markets is carried out. To assess physical risk, the impact of various environmental factors is explored. They are selected based on the guidelines by European regulatory bodies, and on reports by the United Nations. A total of six indices is considered, representing temperature, floods, droughts, wind speed in two directions, and wildfire risk. A special focus is then placed on transition risk,

Table 11
Significant relationships with the transition risk proxies, for German issuers (α = 0.05)

			ECF	TRI 20y
AAREAL BANK AG	Green bonds	Avg. Coeff.	0.0649	
		S/Total	2/2	0/2
	Non-green bonds	Avg. Coeff.		0.0133
		S/Total	0/7	1/7
AMPRION GMBH	Green bonds	Avg. Coeff.	0.1005	−0.0314
		S/Total	1/2	2/2
	Non-green bonds	Avg. Coeff.		−0.0438
		S/Total	0/1	1/1
BAYWA AG	Green bonds	Avg. Coeff.		0.0198
		S/Total	0/1	1/1
DEUTSCHE WOHNEN SE	Green bonds	Avg. Coeff.		−0.0196
		S/Total	0/2	1/2
	Non-green bonds	Avg. Coeff.	0.0392	−0.0499
		S/Total	1/13	3/13
DZ HYP AG	Green bonds	Avg. Coeff.	0.1009	
		S/Total	1/1	0/1
EEW ENERGY FROM WASTE GMBH	Green bonds	Avg. Coeff.	0.0104	
		S/Total	1/1	0/1
EUSOLAG EUROPEAN SOLAR AG	Green bonds	Avg. Coeff.		0.0566
		S/Total	0/1	1/1
HAMBURGER HOCHBAHN AG	Green bonds	Avg. Coeff.		−0.0149
		S/Total	0/1	1/1
ING DIBA AG	Green bonds	Avg. Coeff.	0.1324	
		S/Total	1/2	0/2
RWE AG	Green bonds	Avg. Coeff.	0.0504	−0.0875
		S/Total	3/5	2/5
	Non-green bonds	Avg. Coeff.		−0.0720
		S/Total	0/2	1/2
UNICREDIT BANK AG	Green bonds	Avg. Coeff.	0.0675	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	0.0370	0.0200
		S/Total	32/209	30/209

Table 12
Significant relationships with the transition risk proxies, for French issuers (α = 0.05).

			ECF	TRI 20y
ARKEMA SA	Green bonds	Avg. Coeff.		−0.0498
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.		0.0440
		S/Total	0/4	1/4
BANQUE FEDERATIVE DU CREDIT MUTUEL SA	Green bonds	Avg. Coeff.	0.0514	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	0.0104	−0.0390
		S/Total	8/64	16/64
BPCE SA	Green bonds	Avg. Coeff.	0.0056	
		S/Total	2/2	0/2
	Non-green bonds	Avg. Coeff.	0.0066	−0.0358
		S/Total	6/77	15/77
BPCE SFH SA	Green bonds	Avg. Coeff.	0.0491	−0.0636
		S/Total	2/3	1/3
BPIFRANCE SA	Green bonds	Avg. Coeff.	0.0556	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	0.0503	−0.0161
		S/Total	9/28	6/28

(*continued on next page*)

Table 12 (*continued*).

			ECF	TRI 20y
CAISSE FRANCAISE DE FINANCEMENT LOCAL SA	Green bonds	Avg. Coeff.	0.0408	
		S/Total	1/1	0/1
CREDIT AGRICOLE CORPORATE AND INVESTMENT BANK SA	Green bonds	Avg. Coeff.		−0.0614
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.	0.0231	−0.0447
		S/Total	4/48	4/48
CREDIT AGRICOLE HOME LOAN SFH SA	Green bonds	Avg. Coeff.	0.0441	
		S/Total	1/1	0/1
CREDIT AGRICOLE SA	Green bonds	Avg. Coeff.		−0.0263
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.	−0.0209	−0.0234
		S/Total	16/93	24/93
ILE-DE-FRANCE MOBILITES	Green bonds	Avg. Coeff.	0.0879	
		S/Total	3/5	0/5
	Non-green bonds	Avg. Coeff.	0.0425	
		S/Total	1/3	0/3
LA BANQUE POSTALE HOME LOAN SFH SA	Green bonds	Avg. Coeff.		−0.1189
		S/Total	0/1	1/1
LA BANQUE POSTALE SA	Green bonds	Avg. Coeff.	0.0387	
		S/Total	1/1	0/1
	Non-green bonds	Avg. Coeff.	0.0381	−0.0279
		S/Total	1/7	1/7
NERVAL SAS	Green bonds	Avg. Coeff.	0.1644	
		S/Total	1/2	0/2
RCI BANQUE SA	Green bonds	Avg. Coeff.		−0.0959
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.		0.0108
		S/Total	0/13	6/13
SCHNEIDER ELECTRIC SE	Green bonds	Avg. Coeff.		−0.0478
		S/Total	0/1	1/1
	Non-green bonds	Avg. Coeff.	0.0475	0.0248
		S/Total	2/5	1/5
SOCIETE GENERALE SFH SA	Green bonds	Avg. Coeff.	0.0495	
		S/Total	2/3	0/3
	Non-green bonds	Avg. Coeff.	0.0602	0.0206
		S/Total	16/53	10/53
SOCIETE NATIONALE SNCF SA	Green bonds	Avg. Coeff.	0.0524	
		S/Total	1/2	0/2
	Non-green bonds	Avg. Coeff.	−0.0190	−0.0116
		S/Total	4/14	3/14
SUEZ SA (FR)	Green bonds	Avg. Coeff.		−0.1025
		S/Total	0/3	2/3
UNIBAIL-RODAMCO-WESTFIELD SE	Green bonds	Avg. Coeff.	0.0229	
		S/Total	2/2	0/2
	Non-green bonds	Avg. Coeff.	0.0398	−0.0373
		S/Total	2/33	4/33
VOLTALIA SA	Green bonds	Avg. Coeff.	0.0413	
		S/Total	1/1	0/1

Table 13
Dependence analysis between ECF and TRI20y.

Method	ECF-TRI
Kendall's Tau	−0.032 (0.186)
Spearman's ρ	−0.049 (0.175)
Pearson	−0.045 (0.212)

Table 14
Dependence analysis between TRI and energy commodities.

Method	TTF vs TRI	Coal vs TRI	Oil vs TRI
Kendall's Tau	−0.036 (0.134)	−0.033 (0.166)	0.001 (0.975)
Spearman's ρ	−0.054 (0.133)	−0.052 (0.144)	0.002 (0.965)
Pearson	−0.016 (0.664)	−0.009 (0.798)	−0.018 (0.616)

Table 15
Dependence between ECF and energy commodities.

Method	TTF vs ECF	Coal vs ECF	Oil vs ECF
Kendall's Tau	0.181 (0.000)	0.114 (0.000)	0.058 (0.016)
Spearman's ρ	0.262 (0.000)	0.168 (0.000)	0.085 (0.018)
Pearson	0.109 (0.002)	0.050 (0.165)	0.076 (0.035)

the most elusive component of climate risk, and the statistical significance of two potential proxies is analyzed, separately: the log-returns of futures on the carbon allowances (ECF) of the European Emissions Trading Scheme and a CDS-based transition risk index proposed in the literature.

In the equity market, only a small number of stocks exhibits a significant relationship with the climate risk proxies, relative to the overall sample size. Among the weather variables considered, flooding emerges as the most impactful—an expected result given its potential to cause direct physical damage and disrupt firm revenues. Moreover, the limited explanatory power of all the regressors is consistent with the efficient market hypothesis, which suggests that daily stock returns are inherently highly difficult to forecast. Furthermore, given the low number of statistically significant relationships, attempts aimed at aggregating issuers by country or by sector do not provide additional insights. As for the transition risk proxies, the number of statistically significant relationships with stock returns is comparable, for both of them, to that of the physical risk proxies. When counting the stocks significantly related to both, the number drops drastically and reaches zero at the 2.5% significance level. Our analysis contributes to the literature by comparing the two transition risk proxies and finds that they are not substitutes for each other, as they are not significantly related to the same issuers. Furthermore, policy makers should be aware of the limited current impact of physical and transition risks on equity pricing, indicating a potential underestimation of climate risks in stock valuations. This should be accounted for, when designing climate-related disclosure frameworks and risk assessment tools in equity investments.

In the bond market, two main results emerge. The first concerns physical risk: for a number of variables, green bonds and non-green bonds of the same country have opposite average coefficient sign. In all cases except one, the disagreement about the sign is such that green bonds have a negative one, while non-green bonds have a positive one. This suggests a different reaction to physical risk by the two bond types: the former reacts in a favorable way to increases in risk, while the latter reacts negatively. We propose a number of explanations, linked to firm-level features as well as investor preferences. Additionally, there is a noticeable difference between the countries in this phenomenon. French and Italian green bonds have a negative average coefficient with many more physical risk proxies than those of Germany. This information expands the current literature on physical climate risk, providing a geographical-level understanding of the market impact of observable weather variables. Policymakers should recognize the varying responses to physical risk across different locations and allow for some degree of country-specific tailoring of climate risk assessments.

The second result concerns transition risk. We find that the average sign of the significant coefficients of the two proxies differs, suggesting that they might be capturing different types of information. This would imply that the TRI 20y incorporates transition risk components that go beyond carbon risk. An analysis of the significant relationships of the two risk proxies with each issuer confirms this hypothesis, revealing that they are connected to almost entirely different sets of bonds. As a consequence, since the TRI 20y index is built from the difference of green and brown CDS spreads with a 20 year horizon, we hypothesize that credit default swaps are currently pricing a transition risk that goes beyond carbon emissions. To our knowledge, this is the first study to uncover empirical evidence of this phenomenon: transition risk is found to be priced in the market, for both proxies, but there is a disconnect between the two. The market perception of brown-firm exposure to transition risk, which should be captured by the TRI 20y index, is not limited to the cost of polluting, which is represented by the ECF log-returns. Furthermore, the two indices are priced differently and by sets of firms which have little overlap. Finally, the Italy and Germany areas show different levels of exposure to them. We therefore perform an empirical analysis of the two transition risk proxies, uncovering the absence of correlation between them and their differing relationship with the energy market.

We then conclude the paper by providing a summary of potential policy implications for the use of regulators. We bring attention to the different treatment of climate risk by equity and fixed-income markets, and to the potential underpricing of climate risk in stock prices. We suggest an approach for identifying these possible awareness gaps and highlight the need for a comprehensive measure of transition risk.

While the present work hopefully provides interesting results for policy makers, it has two main limitations, which are particularly relevant in light of future extensions. The first is the geographical coverage of the analysis, which is currently restricted to a selection of European markets. Future work should consider more countries and potentially more regions, which, in light of different geographical features, regulatory environments, and market dynamics, could offer interesting insights. The second concerns the significance of the two transition risk proxies: we hypothesize that the transition risk priced by credit default swaps goes beyond

Table 16
TEGARCH(1,1) ECF and Climate Variables.

Company	ECF	Temp	Flood	Drought	Wind E/W	Wind N/S	FWI	R^2	Country
ASCOPIAVE	−0.015***	−0.0001	0.0006**	0.0004	−0.0005	0.0	0.0001	0.0369	IT
EDISON RSP	0.004	0.0002	−0.0001	−0.008***	0.0002	0.0001	−0.0	0.0001	IT
FIDIA	−0.0148	−0.0003	0.0019***	0.0032	0.0009	0.0014	0.0002	0.0026	IT
BORGOSESIA	−0.0139	0.0002	0.0006**	−0.0039	−0.0002	0.0009	−0.0001	0.0453	IT
SOL	−0.0009	−0.0	−0.0007**	−0.0026	−0.0013***	0.0008	−0.0	0.03	IT
ARKEMA	0.037***	0.0005	−0.0143	−0.003	0.0003	−0.0006	−0.0	0.018	FR
CARBIOS	0.0715**	0.001	0.0135	0.0241	0.0003	0.0006	−0.0001	0.0263	FR
DELFINGEN	0.0025	−0.0006	0.0022	−0.0077***	0.0007	−0.0006	0.0001	0.0442	FR
MICHELIN	0.0257***	0.0002	0.0111	0.001	0.0004	−0.0006	0.0001	0.0149	FR
EO2	−0.0096	−0.001	−0.0884***	−0.0037	0.0004	−0.0005	−0.0003	0.0251	FR
PHOENIX SOLAR	−0.0411	−0.0002	−0.0023**	0.0077***	0.0001	−0.0001	−0.0014*	0.0594	DE
GLOBAL PVQ	0.0547***	−0.0001	−0.0013*	0.0006***	−0.0001***	0.0	−0.0002***	0.1583	DE
SFC ENERGY	−0.0247	−0.002*	−0.0005	−0.0049	−0.0	−0.0035***	0.0001	0.0648	DE
CROPENERGIES	−0.0303	−0.0005	0.0008**	0.0003	0.0002	−0.0001	−0.0001	0.0414	DE
VERBIO	−0.1187**	−0.0008	0.0005	0.0039	−0.0007	−0.0009	0.0005	0.0125	DE
ENVITEC BIOGAS	0.0251	−0.0019***	−0.0007***	−0.0036	−0.0005	−0.0005	0.0011	0.0327	DE
CENTROTHERM PHTO.	−0.065	−0.0012*	−0.0004	−0.0099	−0.0002	0.0003	−0.0017	0.0589	DE
LANXESS	0.0363	−0.0012***	−0.0014***	−0.003	−0.0007	0.0009	−0.0001	0.0201	DE
WACKER CHEMIE	0.0421	−0.001	−0.0006	−0.0114***	−0.0005	−0.0003	0.0003	0.0163	DE
BRENNTAG	0.0002	−0.0004	0.0006***	−0.0001	−0.0003	−0.0006*	0.0002	0.0857	DE
ALZCHEM	0.0041	−0.0003	−0.0007***	0.0005	−0.0001	−0.0005	−0.0002	0.0305	DE
EVONIK INDUSTRIES	−0.0143	−0.0002	−0.001**	−0.0005	−0.0	0.0	−0.0002	0.0238	DE
H & R	0.0309	−0.0003	0.0008***	−0.0091**	0.0001	−0.0001	0.0004	0.0587	DE
SAF-HOLLAND	0.0362	−0.0002	−0.0017***	−0.003	0.0007	−0.0011	0.0003	0.0507	DE
MERCEDES-BENZ GROUP N	0.0246	−0.0008*	−0.0009	0.0008	−0.0006	−0.0008	0.0004	0.0131	DE
ELRINGKLINGER N	0.0403	−0.0016**	−0.0011	−0.0075	0.0012	0.0009	0.0002	0.0792	DE
GRAMMER	−0.0155	0.0	0.0009***	0.0076	0.0002	0.0008	0.0	0.0579	DE
BMW	−0.0019	−0.001***	−0.0005	0.0002	−0.0002	−0.0	−0.0001	0.0138	DE
CONTINENTAL	0.0339	−0.001***	−0.0013	−0.0081	−0.0005	0.0005	0.0005	0.0088	DE
PORSCHE AML.HLDG.PREF.	0.0162	−0.0009*	−0.0003	0.0008	0.0002	−0.0013	0.0003	0.0208	DE
E ON N	0.0053	−0.0	−0.0017***	0.0005	−0.0001	−0.0003	−0.0	0.0131	DE
DEUTSCHE ROHSTOFF	0.0199***	−0.0004	0.0012*	0.0264	0.0003	0.0005	−0.0009	0.0318	DE
META WOLF	−0.0387	−0.0009	−0.0041*	−0.0033	−0.0003	0.0008	−0.0002	0.1013	DE
STO PREFERENCE	−0.0205	0.0002	−0.0008***	−0.0031	0.0002	−0.0008	0.0004	0.0771	DE
STEICO	0.0247***	−0.0003	−0.002***	0.0095	−0.0	−0.0011	−0.0001	0.0723	DE
UZIN UTZ	−0.0278	0.0004	−0.0008***	−0.0122***	0.0003	0.0003	0.0001	0.0555	DE
HOCHTIEF	0.0307	−0.0002	−0.0012*	0.0016	−0.0002	−0.0008	0.0001	0.0244	DE
STEULER FLIESENGRUPPE	−0.0	0.0	−0.0	0.0001**	−0.0**	−0.0	0.0	0.0001	DE
BAUMOT GROUP	0.0159***	−0.0003	0.0001	−0.0032	0.0006***	0.0012***	0.0	0.013	DE
ENBW ENGE.BADEN-WURTG.	0.0012	0.0	−0.0014*	0.0005	0.0006	0.0013*	−0.0002	0.0466	DE
COMPAGNIE D ENTREPRISES CFE	−0.0389*	−0.0005	−0.0001	−0.0044	−0.0001	−0.0001	0.0005*	0.0422	BE
OMV	0.0283	−0.0009**	0.001	0.0015	0.0008	0.0007	0.0003	0.0159	AT
KENDRION	0.0024	−0.0002	0.0037	0.0085	0.0005**	−0.0001	0.0	0.0699	NL
COLUMBUS ENERGY	0.0532	0.0002	0.0184	−0.0148***	−0.0001	0.0002	0.0001	0.0053	PL
SELENA FM SR.B I C	0.0141	0.0	−0.1145	−0.0145***	0.0002	0.0003	0.0	0.0144	PL
GALVO	0.033*	−0.0001	−0.0918	−0.0106	0.0003	−0.0004	0.0006**	0.0595	PL
RAWLPLUG	0.0416	−0.0001	−0.0287	−0.0109*	0.0008	−0.0012	−0.0001	0.0384	PL
COMPREMUM	0.0066	0.0001	0.0219	−0.0142*	−0.0002	0.0003	−0.0002	0.0092	PL
MOBRUK	0.0381	0.0002	0.0266***	0.0115	−0.0007	−0.0003	0.0002	0.0291	PL
PKA.GRUPA ENERGETYCZNA	−0.0759	0.0	−0.1368	−0.0129***	−0.0	0.0004	−0.0003	0.0212	PL
PHOTON ENERGY	0.0054	−0.0011**	0.0216	0.0062	0.0	0.0002	0.0004***	0.0069	NL
IZOSTAL	0.0371***	−0.0004	0.0159	−0.0063	0.0003	0.0003	0.0003	0.0281	PL
BOWIM	−0.0165	0.0002	0.172*	−0.0054	0.0001	0.0001	0.0004	0.0086	PL
BALTICON	−0.0089**	−0.0	0.0574	−0.0051	0.0001	0.0002	0.0	0.0313	PL
FORPOSTA	−0.0067	0.0	0.0078	−0.0122***	0.0001	0.0001	−0.0	0.0065	PL
ERCROS	0.0173	0.0001	−0.0878***	0.0176	−0.0007	−0.0006	−0.0001	0.034	ES
EDP RENOVAVEIS	−0.0409	0.0003	0.1291**	−0.0157	0.0006	0.0006	0.0	0.027	ES

Table 17
TEGARCH(1,1) TRI20y and Climate Variables.

Company	TRI20y	Temp	Flood	Drought	Wind E/W	Wind N/S	FWI	R^2	Country
ASCOPIAVE	0.0014	−0.0002	0.0006*	0.0003	−0.0005	0.0	0.0001	0.0367	IT
ACEA	−0.0012	−0.0005	0.0004***	−0.0016	0.0003	−0.0004	−0.0002	0.0161	IT
FRENDY ENERGY	−0.0018	−0.0004*	−0.0002	−0.0005	0.0009	−0.0009	−0.0001	0.0196	IT
FIDIA	−0.0073	−0.0004	0.0019***	0.0033	0.0009	0.0013	0.0003	0.0027	IT
SOL	−0.0114	−0.0	−0.0007**	−0.002	−0.0013	0.0008	−0.0	0.0367	IT
L AIR LQE.SC.ANYME. POUR L ETUDE ET L EPXTN.	−0.0062	0.0001	0.0097	−0.0054*	0.0004	−0.0001	0.0002**	0.0446	FR
VEOLIA ENVIRON	−0.0128**	0.0003	0.0374	0.0061	0.0007	−0.0004	0.0002	0.0427	FR
ENGIE	−0.0123***	−0.0	−0.0054	−0.0017	0.0006	−0.0001	0.0003	0.0283	FR
MAUREL ET PROM	−0.0104	−0.0009	−0.0338	0.0296*	−0.0006	−0.0008	−0.0	0.0178	FR
SIGNAUX GIROD	0.0058	−0.0008*	−0.0371	−0.0181	0.0002	0.0001	0.0	0.0189	FR
EO2	−0.0162	−0.0009**	−0.0838***	−0.0084	0.0005	−0.0004	−0.0003	0.0276	FR
SOLARWORLD K	−0.0017	0.0001	0.0057***	0.0262*	0.0005	−0.0004	−0.0004	0.0158	DE
PHOENIX SOLAR	−0.0214***	−0.0001	−0.0024	0.0089***	0.0005	−0.0001	−0.0012***	0.0605	DE
GLOBAL PVQ	−0.0005*	0.0002***	−0.0012	−0.0004***	0.0002***	0.0003***	−0.0005*	0.1588	DE
SFC ENERGY	0.0031	−0.002*	−0.0005	−0.0056	−0.0	−0.0035***	0.0002	0.0638	DE
CROPENERGIES	−0.0012	−0.0006	0.0008**	0.0001	0.0002	−0.0001	−0.0001	0.0378	DE
VERBIO	0.0177***	−0.0009	0.0006	0.003	−0.0008	−0.0008	0.0007	0.0044	DE
ENVITEC BIOGAS	−0.0037	−0.002***	−0.0007***	−0.0037	−0.0005	−0.0005	0.001	0.0318	DE
ENAPTER	−0.0078	−0.0003	0.0013***	−0.0101	−0.0003	−0.0019	0.0	0.0245	DE
LANXESS	0.0012	−0.0012***	−0.0013***	−0.0034	−0.0007	0.0009	−0.0001	0.0168	DE
MUEHLHAN	0.0026	0.0003	−0.0004***	−0.0025**	0.0006	0.0003	−0.0001	0.0678	DE
NABALTEC	−0.0006	0.0001	−0.0012***	0.0045	0.0004	−0.0003	0.0003	0.0402	DE
SYMRISE	−0.0065	−0.0003	−0.0005**	−0.0061	0.0002	−0.0004	−0.0001	0.0723	DE
BRENNTAG	0.0114	−0.0004	0.0006***	−0.0007	−0.0003	−0.0006	0.0003	0.089	DE
ALZCHEM	0.0062	−0.0003	−0.0007***	0.0005	−0.0	−0.0005	−0.0001	0.0314	DE
EVONIK INDUSTRIES	−0.0035	−0.0002	−0.001***	−0.0003	−0.0001	0.0	−0.0002	0.025	DE
BASF	−0.0073	−0.0006***	−0.0017***	0.0045	−0.0005	0.0005	−0.0002	0.0043	DE
SAF-HOLLAND	0.002	−0.0002	−0.0017***	−0.0032	0.0007	−0.0012	0.0003	0.0497	DE
MERCEDES-BENZ GROUP	−0.0126	−0.0007*	−0.0009	0.0005	−0.0005	−0.0007	0.0004	0.0149	DE
BMW	0.0026	−0.0009***	−0.0005	0.001	−0.0002	−0.0	−0.0001	0.0141	DE
CONTINENTAL	0.0048	−0.001***	−0.0011	−0.0078***	−0.0004	0.0005	0.0005	0.0107	DE
PORSCHE AML.HLDG.PREF.	−0.0042	−0.0008*	−0.0001	0.0033	−0.0	−0.0013*	0.0002	0.0186	DE
FERNHEIZWERK NEUKOLLN	−0.0003	0.0002	−0.0004**	0.0064	−0.0005	0.0001	0.0001	0.0649	DE
E ON N	0.0057	−0.0	−0.0017***	0.0006	−0.0001	−0.0003	−0.0	0.0082	DE
DEUTSCHE ROHSTOFF	−0.0023	−0.0004	0.0012*	0.0265	0.0003	0.0005	−0.0009	0.0319	DE
STEICO	0.0227	−0.0003	−0.0018***	0.0088	0.0	−0.0012	−0.0001	0.077	DE
INNOTEC TSS	0.0129	−0.0007	−0.0015***	−0.0014	0.0001	0.0005	0.0003	0.153	DE
UZIN UTZ	0.0126	0.0003	−0.0007**	−0.014	0.0002	0.0003	0.0001	0.0551	DE
HOCHTIEF	0.0002	−0.0002	−0.0012***	0.0018	−0.0002	−0.0008	0.0001	0.0258	DE
MVV ENERGIE	−0.0081	−0.0002	0.0013***	0.0015	0.0007	0.0002	0.0	0.0654	DE
FLORIDIENNE	−0.0168***	−0.0002	0.0022***	0.006	0.0002	0.0002	0.0002***	0.0092	BE
BURGENLAND HOLDING	−0.0005	−0.0	0.0**	−0.0005***	0.0002	−0.0	0.0001	0.0055	AT
OMV	−0.0024	−0.0009**	0.0011	0.0016	−0.0003	0.0019	0.0003	0.0162	AT
KENDRION	−0.0082***	−0.0002	0.0049	0.009*	0.0005	−0.0001	0.0	0.0717	NL
KON.HEIJMANS DU. CERTS.	−0.0122***	−0.0001	0.0177	0.0084	0.0007	−0.0007	−0.0	0.0191	NL
AMG CRITICAL MATERIALS	−0.0242***	−0.0005	−0.1073	0.0026	0.0003	−0.0009	0.0002*	0.0304	NL
COLUMBUS ENERGY	0.0043	0.0002	0.0231	−0.0147*	−0.0031	0.0033	0.0002	0.0089	PL
GALVO	−0.004***	−0.0001	−0.0943	−0.0095*	0.0004	−0.0005	0.0006	0.059	PL
IZOBLOK	0.0022	0.0003*	−0.0105	−0.0055	0.0005	−0.001	0.0001	0.0104	PL
MOSTAL	−0.0044	−0.0001	−0.0678***	−0.0103	0.0007	−0.0009	−0.0003	0.0189	PL
INSTAL KRAKOW	−0.0215***	0.0002	0.0203	0.0041	0.0003	0.0001	0.0	0.0163	PL
EC BEDZIN	−0.0038	−0.0009**	−0.0318	−0.0072	−0.0113	0.0106	−0.0002	0.0161	PL
ZESPOL ELKTP. WRLKKNR.	0.0098	0.0003**	0.0135	0.0115***	−0.0002	−0.0002	0.0003	0.0262	PL
PHOTON ENERGY	−0.0092	−0.0011**	0.0198	0.0064	−0.0001	0.0002	0.0004***	0.0085	NL
KCI	−0.0043**	0.0002	−0.0427***	0.0103***	−0.0018	0.0003	−0.0003	0.0172	PL
ZAKLADY MAGNEZYTOWE ROPCZYCE	0.0181***	−0.0002	−0.0431	−0.0118	−0.0001	0.0001	0.0	0.0525	PL
NATURGY ENERGY	0.0025	0.0002	−0.0055*	0.0001	0.0001	0.0	0.0	0.0071	ES
EDP RENOVAVEIS	−0.004	0.0004	0.1236***	−0.0146	0.0006	0.0006	0.0	0.0252	ES

carbon emissions, but further research should be carried out to investigate this theory. Attempts should be made to identify the potential drivers of the difference between the two, potentially recognizing the role of evolving market sentiment and belief about transition risk scenarios and upcoming policies.

CRediT authorship contribution statement

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

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Appendix

A.1. Complete list of stocks analyzed

Hera (IT), Acinque (IT), Ascopiave (IT), Edison Rsp (IT), Italgas (IT), Convergenze (IT), Alerion Clean Power (IT), Enel (IT), Terna Rete Elettrica Naz (IT), Algowatt (IT), Acea (IT), A2 A (IT), Frendy Energy (IT), Erg (IT), Iniziative Bersa (IT), Agatos (IT), Comal (IT), Eviso (IT), Altea Green Power (IT), Rocket Sharing (IT), Gas Plus (IT), Eni (IT), Biesse (IT), Fidia (IT), Tesmec (IT), Borgosesia (IT), Interpump Group (IT), Clabo (IT), Gel (IT), Esautomotion (IT), Vimi Fasteners (IT), Piovan (IT), Ilpra (IT), Comer Industries (IT), Marzocchi Pompe Spa (IT), Osai Automation System (IT), Tenax International (IT), Cofle (IT), Iveco Group (IT), Sbe Varvit (IT), Innovatec (IT), Enertronica (IT), Ecosuntek (IT), Renergetica Dead - Delist.08/02/24 (IT), Esi (IT), Aton Green Storage (IT), Lemon Sistemi (IT), Sol (IT), Aquafil (IT), Industrie Chimiche Forestali (IT), Magis (IT), Green Oleo (IT), Encres Dubuit (FR), Orapi (FR), Arkema (FR), Metabolic Explorer (FR), Fermentalg (FR), Robertet (FR), L Air Lqe.Sc.Anyme. Pour L Etude Et L Epxtn. (FR), Explos.Et Prds.Chim. (FR), Carbios (FR), Amoeba (FR), Baikowski (FR), Afyren (FR), Groupe Berkem (FR), Akwel (FR), Renault (FR), Streit Mecanique (FR), Burelle (FR), Delfingen (FR), Michelin (FR), Valeo (FR), Plastic Omnium (FR), Forvia (FR), Hopium (FR), Veolia Environ (FR), Engie (FR), Finaxo Environnement (FR), Eaux De Royan (FR), Osmosun (FR), Maurel Et Prom (FR), Dynex Energy (FR), Sequa Petroleum (United Kingdom), Totalenergies Ep Gabon (Gabon), Clean Logistics *N* (DE), Totalenergies (FR), Cie De Chemins De Fer Departementaux (FR), Trilogiq (FR), Metalliance Susp - Susp.30/01/24 (FR), Roctool (FR), Exail Technologies (FR), Signaux Girod (FR), Hydraulique Pb (FR), Cerinnov Group (FR), Balyo (FR), Boa Concept (FR), Stif (FR), Eo2 (FR), Vergnet Vsa (FR), Jsa Technology Susp - Susp.11/03/24 (FR), Weya (FR), Global Bioenergies (FR), Mcphy Energy (FR), Nhoa (FR), Enertime Sas (FR), Blue Shark Power (FR), Boostheat (FR), Enogia (FR), Entech (FR), Waga Energy Prom (FR), Haffner Energy (FR), Lhyfe Promesses (FR), Nordex (DE), Solarworld K (DE), Phoenix Solar (DE), Global Pvq (DE), Sfc Energy (DE), Cropenergies (DE), Verbio (DE), Envitec Biogas (DE), Centrotherm Phto. (DE), Sma Solar Technology (DE), Enapter (DE), Clearvise (Fra) (DE), Abo Wind (DE), Tion Renewables Dead - Delist.17/04/24 (DE), Tubesolar (DE), Siemens Energy *N* (DE), Ccs Abwicklungs (DE), Thyssenkrupp Nucera (DE), Abo Kraft & W Rme *N* (DE), Masterflex (DE), Lanxess (DE), Wacker Chemie (DE), Muehlhan (DE), Nabaltec (DE), Symrise (DE), Fuchs *N* (DE), Brenntag (DE), Eckert & Ziegler (DE), Alzchem (DE), Evonik Industries (DE), Basf (DE), H & R (DE), Covestro (DE), Brain Biotech *N* (DE), Decheng Technology K (DE), Delticom (DE), Saf-Holland (DE), Mercedes-Benz Group *N* (DE), Elringklinger *N* (DE), Grammer (DE), Volkswagen (DE), Hella Gmbh & Kgaa (DE), Bmw (DE), Continental (DE), Porsche Aml.Hldg.Pref. (DE), Schaeffler Pf.Shs. (DE), Jost Werke (DE), Voltabox (DE), Sts Group (DE), Fox E-Mobility (Dus) (DE), Hgears (DE), Novem Group (Luxembourg), Vitesco Technologies Group *N* (DE), Elaris Par (DE), Dr Ing Hc F Porsche Pref. (DE), Ari Motors Industries (DE), Fernheizwerk Neukolln (DE), Mainova (DE), Rwe (DE), E On *N* (DE), Gelsenwasser (DE), Uniper K (DE), Global Oil & Gas (DE), Deutsche Rohstoff (DE), Aee Gold (DE), Petronor E&P (Norway), Meta Wolf (DE), Sto Preference (DE), Bauer (DE), Steico (DE), Villeroy & Boch Pf.Shs. (DE), Innotec Tss (DE), Uzin Utz (DE), Hochtief (DE), Westag (DE), Steuler Fliesengruppe (DE), Nexus Infrastructure (United Kingdom), Libero Football Finance (DE), Semodu *N* (DE), 7C Solarparken K (DE), Energiekontor (DE), 4 Sc (DE), Baumot Group (DE), 2G Energy (DE), Encavis (DE), Pne (DE), Mvv Energie (DE), Carpevigo Holding (DE), Lechwerke (DE), Enbw Enge.Baden-Wurtg. (DE), Name (Nation), Ekopak (BE), Moury Construct (BE), Compagnie D Entreprises Cfe (BE), Etex (BE), Scr- Sibelco (BE), Aliaxis (BE), Compagnie Het Zoute (BE), Kabelwerk Eupen (BE), Fimmobel (BE), Floridienne (BE), Bekaert (D) (BE), Jensen-Group (BE), Evn (AT), Burgenland Holding (AT), Verbund (AT), Rath (AT), Strabag Se (AT), Zumtobel (AT), Sw Umwelttechnik (AT), Porr (AT), Hutter & Schrantz (AT), Wienerberger (AT), Polytec Holding (AT), Omv (AT), Mt Hoejgaard Holding (Denmark), H+H International (Denmark), Rockwool B (Denmark), Flsmidth And Co. (Denmark), Scandinavian Brake Sys. (Denmark), Ennogie Solar Group (Denmark), Vestas Windsystems (Denmark), Green Hydrogen Systems (Denmark), Uie (Malta), Firstfarms (Denmark), Schouw And (Denmark), Glunz & Jensen Holding (Denmark), Brd Klee B (Denmark), Skako (Denmark), Nilfisk Holding (Denmark), Odico Dead - Delist.21/03/24 (Denmark), Scape Technologies (Denmark), Fom Technologies (Denmark), Kobenhavns Lufthavne (Denmark), Dsv (Denmark), Erria (Denmark), Torm A (United Kingdom), Dmpkbt.Norden (Denmark), Ntg Nordic Transport Group (Denmark), Dfds (Denmark), A P Moller Maersk B (Denmark), Greenmobility (Denmark), Kendrion (NL), Sif Holding (NL), Fastned Dutch Certificates (NL), Kon.Heijmans Du. Certs. (NL), Bam Groep Kon. (NL), Signify (NL), Ferrovial (NL), Cabka (NL), Amg Critical Materials (NL), Hydratec Industries (NL), Ebusco Holding (NL), Sbm Offshore (NL), Sunex (PL), Mva Green Energy (PL), Columbus Energy (PL), Voolt (PL), Viatron Dead - Delist.13/02/24 (PL), Biomass Energy Project (PL), Termo2Power (PL), Ml System (PL), Zeneris Projekty (PL), Firma Oponiarska Debica (PL), Inter Cars (PL), Less (PL), Ac Autogaz (PL), Pl Group (PL), Orzel (PL), Solar Innovation (PL), Auto Partner (PL), Triggo (PL), Krakchemia (PL), Selena Fm Sr.B I C (PL), Galvo (PL), Hortico (PL), Izoblok (PL), Szar (PL), Prymus (PL), Pcc Exol (PL), Pcc Rokita (PL), Polwax (PL), Kgl (PL), Advanced Graphene Products (PL), Mostostal Zabrze (PL), Budimex (PL), Pbg (PL), Rawlplug (PL), Mostostal Warszawa (PL), Lena Lighting (PL), Decora (PL), Erbud (PL), Investment Friends (Estonia), Mercor (PL), Pa Nova (PL), Resbud (Estonia), Izolacja Jarocin (PL), Trakcja (PL), Unibep (PL), Starhedge (PL), Compremum (PL), Mirbud (PL), Fon (Estonia), Mostal (PL), Instal Krakow (PL), Mera (PL), Tesgas (PL), Zue (PL), Libet (PL), Megaron (PL), Tamex Obiekty Sportowe (PL), Mobruk (PL), Interma Trade (PL), Dektra (PL), Internity (PL), Honey Payment Group (PL), Przed.Prz.Betonow Prefabet Biale Blota (PL), Rocca (PL), Fabryka Konstrukcji Drew (PL), Ulma Constr.Polska (PL), Atlantis (Estonia), Polimex Mostostal (PL), Torpol (PL), Forbuild (PL), Hm Inwest Ord (PL), Dekpol (PL), Pekabex (PL), Tower Investments (PL), Ekopark (PL), Tauron Polska Energia (PL), Ec Bedzin (PL), Pka.Grupa Energetyczna (PL), Enea (PL), Polenergia (PL), Zespol Elktp. Wrlkknr. (PL), Ze Pak (PL), Energa (PL), Photon Energy (NL), Unimot (PL), Mangata Holding (PL), Zak Ad Bud Maszyn Zbc. (PL), Kupiec (PL), Boryszew (PL), Fabryka Obrabiarek Rafamet (PL), Zaklady Urzadzen Kotlowych Staporkow (PL), Moj (PL), Pgf Polska Grupa Fotowoltaiczna (PL), Energoinstal (PL), Secogroup (PL), Wielton (PL), Bumech (PL), Kci (PL), Zaklady Magnezytowe Ropczyce (PL), Patentus (PL), Hydrapres (PL), Zamet (PL), Sanok Rubber Company (PL), Feerum (PL), Aps Energia (PL), Aqt Water (PL), Drozapol Profil (PL), Pjp Makrum (PL), Odlewnie Polskie (PL), Izostal (PL), Bowim (PL), Grupa Kety (PL), Mfo (PL), Ekopol Gornoslask Hldg. (PL), Stalprodukt (PL), Stalexport Autostrady (PL), Transpol (PL), Ot Logistics (PL), Balticon (PL), Forposta (PL), Kdm Shipping (PL), Xbs Pro-Log (PL), Pkp Cargo (PL), Pointpack Pl (PL), Naturgy Energy (ES), Grino Ecologic (ES), Soltec Power Holdings (ES), Profithol (ES), Umbrella Solar Investment (ES), Grupo Greening 2022 (ES), Ercros (ES), Plasticos Compuestos (ES), Obrascon Huarte Lain (ES), Fluidra (ES), Acs Activ.Constr.Y Serv. (ES), Fomento Constr.Y Cntr. (ES), Acciona (ES), Sacyr (ES), Clerhp Estrctur (ES), Asturiana De Laminados (ES), Audax Renovables (ES), Solaria Energia Y Medio Ambiente (ES), Edp Renovaveis (ES), Redeia Corporacion (ES), Endesa (ES), Akiles Corporation (Bulgaria), Iberdrola (ES), Grenergy Renovables (ES), Grupo Ecoener U (ES), Corporacion Acciona Energias Renovables (ES), Opdenergy Holding Dead - Delist.18/04/24 (ES), Energy Solar Tech (ES), Romande Energie (Switzerland), Edisun Power Europe *N* (Switzerland), Bkw (Switzerland), Energiedienst Holding (Switzerland), Clariant (Switzerland), Givaudan 'N' (Switzerland), Dottikon Es Holding (Switzerland), Gurit Holding 'B' (Switzerland), Ems-Chemie 'N' (Switzerland), Feintool (Switzerland), Autoneum Holding (Switzerland)

A.2. Complete list of bonds issuers

Credit Agricole Italia Spa (IT), Acea Spa (IT), Aeroporti Di Roma Spa (IT), Alerion Clean Power Spa (IT), Alperia Spa (IT), Assicurazioni Generali Spa (IT), A2 A Spa (IT), Banco Bpm Spa (IT), Cassa Depositi E Prestiti Spa (IT), Erg Spa (IT), Ferrovie Dello Stato Italiane Spa (IT), Hera Spa (IT), Intesa Sanpaolo Spa (IT), Iren Spa (IT), Leasys Spa (IT), Mediobanca Banca Di Credito Finanziario Spa (IT), Snam Spa (IT), Terna Rete Elettrica Nazionale Spa (IT), Unipol Gruppo Spa (IT), Aareal Bank AG (DE), Aoc I Die Stadtentwickler Gmbh (DE), Bayerische Landesbank (DE), Berlin Hyp AG (DE), Commerzbank AG (DE), Deutsche Bank AG (DE), Deutsche Kreditbank AG (DE), Deutsche Pfandbriefbank AG (DE), Dz Bank AG Deutsche Zentral Gnossbk Frankfurt Am Main (DE), Dz Hyp AG (DE), Eusolag European Solar AG (DE), Greencells Gmbh (DE), Ing Diba AG (DE), Landesbank Baden Wuerttemberg (DE), Landesbank Hessen Thueringen Girozentrale (DE), Landesbank Saar (DE), Momox Holding Gmbh (DE), Muenchener Hypothekenbank Eg (DE), Norddeutsche Landesbank Girozentrale (DE), Nrw Bank (DE), Procredit Holding AG & Co Kgaa (DE), Reconcept Gmbh (DE), Reconcept Green Energy Asset Bond Ii Gmbh (DE), Unicredit Bank AG (DE), Amprion Gmbh (DE), Basf Se (DE), Baywa AG (DE), Deutsche Wohnen Se (DE), Dic Asset AG (DE), E On Se (DE), Eew Energy From Waste Gmbh (DE), Eurogrid Gmbh (DE), Evonik Industries AG (DE), Ewe AG (DE), Hamburger Hochbahn AG (DE), Kfw (DE), Landwirtschaftliche Rentenbank (DE), Mbt Systems Gmbh (DE), Mercedes Benz Group AG (DE), Novelis Sheet Ingot Gmbh (DE), Rwe AG (DE), Senvion Holding Gmbh (DE), Vonovia Se (DE), Zf Finance Gmbh (DE), Agence Francaise De Developpement Epic (FR), Air Liquide Finance Sa (FR), Ald Sa (FR), Arkema Sa (FR), Banque Federative Du Credit Mutuel Sa (FR), Bnp Paribas Sa (FR), Bpce Sa (FR), Bpce Sfh Sa (FR), Bpifrance Sa (FR), Caisse Francaise De Financement Local Sa (FR), Caisse Nationale De Reassurance Mutuelle Agr Groupama (FR), Compagnie De Phalsbourg Sarl (FR), Covivio Sa (FR), Credit Agricole Corporate And Investment Bank Sa (FR), Credit Agricole Home Loan Sfh Sa (FR), Credit Agricole Sa (FR), Derichebourg Sa (FR), Electricite De France Sa (FR), Engie Sa (FR), Faurecia Se (FR), Gecina Sa (FR), Getlink Se (FR), Icade Sa (FR), Ile-De-France Mobilites (FR), La Banque Postale Home Loan Sfh Sa (FR), La Banque Postale Sa (FR), La Poste Sa (FR), Natixis Sa (FR), Nerval Sas (FR), New Immo Holding Sa (FR), Orpea Sa (FR), Rci Banque Sa (FR), Schneider Electric Se (FR), Sfil Sa (FR), Sncf Reseau Sa (FR), Societe Du Grand Paris (FR), Societe Generale Sfh Sa (FR), Societe Nationale Sncf Sa (FR), Suez Sa (FR), Unibail-Rodamco-Westfield Se (FR), Voltalia Sa (FR).

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