Empirical Economics
https://doi.org/10.1007/s00181-023-02416-8

Climate transition risk in determining credit risk: evidence from firms listed on the STOXX Europe 600 index

Daniel Ramos-García[1] · **Carmen López-Martín**[1] · **Raquel Arguedas-Sanz**[1]

Received: 20 March 2022 / Accepted: 17 March 2023

Abstract

This paper assesses whether a climate factor is relevant to measure default risk in a sample of main companies listed on the STOXX Europe 600 exchange from 2010 to 2020. The starting point is a factorial panel data model which is subsequently modified to capture the climate impact through different functional forms. We find that relevant differences in default risk exist before and after the Paris Agreement. Our analysis also indicates that this difference cannot be explained by means of traditional financial factors. Finally, we further show that a climate change risk and opportunities label is a significant factor in evaluating credit risk, both prior to and post-Paris agreement. These results are important to the extent that they suggest that companies' market performance itself allows to measure differences in credit risk between companies and to link them with climate risk factors. This approach may be useful as a complement or in combination with the traditional use of exogenous climate factors that have been widely used in the literature in this field.

Keywords Credit risk · Climate risk · Distance to default · Transition risk

Mathematical Subject Classification G14 · G38 · Q51 · Q54 · M14

Daniel Ramos-García, Carmen López-Martín and Raquel Arguedas-Sanz have contributed equally to this work.

✉ Carmen López-Martín
carmen.lopez@cee.uned.es

Daniel Ramos-García
dramos145@alumno.uned.es

Raquel Arguedas-Sanz
rarguedas@cee.uned.es

[1] Economics and Business Administration Faculty, National Distance Education University (UNED), Senda del Rey 11, 28040 Madrid, Spain

Published online: 10 April 2023

1 Introduction

The COVID pandemic, declared in January 2020, has led to an unprecedented reduction in economic activity, which has consequently triggered a significant reduction in greenhouse gas emissions, this decline being six times greater than that seen after the financial crisis of 2009 (International Energy Agency 2020).[1] This can be explained by the fact that economic growth is linked to an increase in carbon emissions (Mardani et al. 2019). Therefore, due to concerns about climate change, the challenge for economic agents, especially policymakers, is to stimulate economic activity to recover the economy and employment levels but without increasing emissions, in order to meet the goals established in the Paris Agreement (UNFCCC 2016).[2]

In this context, a significant number of initiatives and bodies have emerged with the aim of promoting the transition from a carbon-intensive economy to a green, low-emissions economy, compatible with the goals of the Paris Agreement.

In the banking sector specifically, the Basel Committee on Banking Supervision (BCBS) has established a working group, known as the Task Force on Climate-related Financial Risks (TFCR), dedicated to developing initiatives to address the integration of the climate dimension into risk management (BCBS 2020). Moreover, different financial supervisors and central banks have developed a network, the so-called Network for Greening the Financial System (NGFS), whose main objective is to tackle climate risk and encourage financial institutions to include the analysis of this risk across all their management frameworks and processes (NGFS 2017). There is also the UNEP FI initiative (UNEP FI 2018), whose task is to assess existing methodologies in order to share best practices identified among participating entities.

All these bodies have been working on defining the theoretical frameworks for the discussion of the transmission channels and main drivers of climate risk (BCBS 2021b; NGFS 2019), but also on an analysis of the available methodologies, including an assessment of the main gaps in current practices within the financial sector (BCBS 2021a; UNEP FI 2019).

The financial sector is a key player in this transformation, not only because of its exposure to climate-related events, but also because of its role as the main conduit of funds. Institutions are expected to incorporate climate risk management into their management framework in the same way as they do for other financial risks. This will affect their business strategy as well as their balance sheets and income statements, both due to transition and for physical reasons (Feridun and Güngör 2020; NGFS, 2019; BCBS 2021).

For example, in the case of the European framework (ECB, 2020), institutions are expected to identify and integrate climate-related risks into default risk quantification, as well as to incorporate such assessment into both management and pricing

[1] Almost 2.6 gigatons (Gt) in 2020 versus 0.4 Gt in 2009 (International Energy Agency 2020).

[2] The Paris Agreement is an international treaty on climate change which 195 countries signed in 2015. Its aim is to limit global warming to 1.5 °C to fulfil the long-term goal of keeping the global average increase at less than 2 °C above its pre-industrial level. The agreement is legally binding and nationally implemented and its main elements are based on the reduction and subsequent elimination of the use of fossil fuels in energy generation and their replacement with clean energy sources.

processes. They are also expected to include the climate dimension in collateral evaluation and in the monitoring of portfolios through stress test exercises and sectoral and/or geographical concentration analyses.

This regulatory concern is partly due to the fact that climate events can be a real source of default risk. As shown in Table 1, several authors have assessed the correlation between sustainability factors and different financial performance indicators, especially in relation to the premium between green and conventional bonds. Some authors have also focused their analyses on the impact that sustainability factors have specifically on credit risk. One common approach is to use carbon emissions to explain changes in distance to default (Capasso et al. 2020; Kabir et al. 2021) or in credit rating (Safiullah et al. 2021).[3] Another way to assess this impact is to use corporate social rating (Zanin 2022) or environmental and social rating (Drago et al. 2019) as an explanatory variable. However, other relevant factors remain largely unexplored. For example, Clarkson et al. (2015) found that both regulatory and market factors are relevant when analysing the impact of carbon emissions on company value.

This paper, therefore, contributes to climate risk factor analysis in credit risk by considering two substantial innovations. The first is the use of a factorial model based on the disparities between the different components of the STOXX Europe 600 index, to observe if there are any co-movements that explain the changes in Merton's distance to default once various sectoral and financial factors have been considered.

The second new approach, consistent with the framework employed by Clarkson et al. (2015), is the definition of a factor climate variable based on the Climate Change Commercial Risks Opportunities indicator to recognise potential differences in the regulatory frameworks and markets and assess differences in credit risk.

For this purpose, a panel data approach is used. It includes financial and sectoral control variables and also a factorial climate variable based on the differences in the evolution of credit risk depending on the classification of the company as having a green or a brown label under the Climate Change Commercial Risks Opportunities label system.

As a result, it can be observed that the climate factor is significant after but also before the signing of the Paris Agreement. It can also be seen that this agreement does not particularly affect the relevance of this factor.

Hence, this paper is organised as follows. Section 2 sets out the literature related to the analysis between environmental variables and credit risk performance indicators, along with a review of the different climate transition risk impact frameworks. In Sect. 3, the main methodological assumptions linked to credit risk measurement approaches and green and brown labelling criteria, as well as the proposed models, are presented. Section 4 contains a discussion of the different outcomes obtained. Finally, Sect. 5 examines the implications of the key findings stemming from this paper.

[3] According to the GHG Protocol WRI (2014): Scope 1: direct emissions occur from sources owned or controlled by the company. Scope 2: indirect emissions are from the generation of purchased energy (electricity, heat or steam). Scope 3: indirect emissions are a result of an organisation's operations but are not owned or controlled by the company.

Table 1 Summary table of papers that contributes to the analysis between climate risk factors and performance indicators:

Authors	Sample (period and population)	Modelling approach	Dependent variable	Transition Risk Proxy	Results (only related to environmental analysis)
Sharfman and Fernando (2008)	1999–2002 267 US firms	Linear regression	Cost of equity (WACC)	Emissions from Toxic Release Inventory	Lower cost of capital for companies with better environmental risk management through lower volatility in terms of market beta
Bauer and Hann (2010)	1995–2006 2,242 bonds	Fixed effects panel data regression	Cost of debt, bond rating and issuer rating	Environmental concerns and strengths	Environmental concerns imply a higher cost of debt and lower credit ratings, while proactive environmental practices imply a lower cost of debt
Nandy and Lodh (2012)	1991–2006 1026 US firms	Fixed effects panel data regression	Price, maturity, loan size, collateral, covenants	Environment score	Better environmental management is related to a more favourable cost of loan
Chava (2014)	1992–2007 5879 Bank loans	Fixed effects panel data regression	Expected stock returns	Environmental concerns (current and expected)	The environmental profile of the firm has an impact on the cost of capital and environmental concerns are related to a higher cost of capital
Oikonomou et al. (2014)	1991–2008 3240 firms	Linear regression	Credit spreads	Corporate social responsibility strengths and concerns	Positive relationship between environmental concerns and credit spread

Table 1 (continued)

Authors	Sample (period and population)	Modelling approach	Dependent variable	Transition Risk Proxy	Results (only related to environmental analysis)
Jung et al. (2018)	2009–2013 78 Australian firms	Pooled cross sections through OLS	Cost of debt	Scope 1 carbon emissions (GHG) and carbon risk awareness (CDP)	A firm's cost of debt will increase with its historical carbon risk profile, but a demonstrated awareness of carbon-related risks will serve to mitigate the penalty
Drago et al. (2019)	2007–2017 184 firms	Pooled cross sections through OLS	Credit Default Swap (CDS)	Corporate social responsibility rating (CSR)	CSR rating upgrade leads to an immediate decrease in CDS spreads of rated firms. In contrast, CSR rating downgrades do not have a significant immediate impact on the CDS
Capasso et al. (2020)	2007–2017 458 firms	Pooled cross sections through OLS	Merton's Distance to Default	Scope 1 carbon emissions (GHG)	Higher level of emissions implies a lower distance to default, ceteris paribus
Ehlers et al. (2021)	2005–2018 567 firms	Fixed effects panel data regression	Margin of interest	Carbon Intensity (scopes 1, 2 and 3)	Scope 1 emissions are priced while other scopes are not

Table 1 (continued)

Authors	Sample (period and population)	Modelling approach	Dependent variable	Transition Risk Proxy	Results (only related to environmental analysis)
Safiullah et al. (2021)	2004–2018 574 firms	Probit regression model	Credit Rating	Direct emissions (scope 1) and indirect emissions (scope 2)	Carbon emissions have a significant negative impact on credit ratings, although the impacts of direct carbon emissions on credit ratings are more pronounced than for indirect carbon emissions
Zanin (2022)	2017–2019 1126 firms	Multivariate ordinal logistic regression	Credit Rating	Environmental, Social and Governance (ESG) ratings	Firms that manage environmental matters better than their industry peers are perceived as more resilient to long-term risks and tend to be rewarded by credit rating agencies
Kabir et al. (2021)	2004–2018 2785 firms	Multivariate regression	Merton's Distance to Default	Total, direct (scope 1) and indirect (scope 2) emissions	Significant and negative impact of emissions on firms' distance-to default. Firms' environmental commitments and green initiatives mitigate the effect while environmental controversies exacerbate it

CDP Carbon Disclosure Project, *GHG* Greenhouse gas, *OLS* Ordinary least squares, *WACC* Weighted Average Cost of Capital

2 Literature review

The existing literature covers the analysis of the relationship between environmental issues and credit risk performance indicators, such as cost of equity (Sharfman and Fernando 2008), loan contract conditions (Nandy and Lodh 2012), cost of debt (Chava 2014) and credit spreads (Oikonomou et al. 2014), showing in all cases that a better environmental performance is associated with better credit performance indicators.

Since 2013, when the first green bond databases became available, many authors have focused their analysis on the interest rate premium differences between green and conventional bonds. Some of them, such as Agliardi and Agliardi (2019), Baker et al. (2022), Ehlers and Packer (2017) and Zerbib (2019), have found a positive green premium, while others such as Hachenberg and Schiereck (2018), Harrison (2019) and Tang and Zhang (2020) have found mixed effects or even no green premium at all. MacAskill et al. (2021) carried out a systematic review of this precise topic, finding that at least a 1–9 green basis point premium exists in the secondary market.

Nevertheless, fewer analyses have focused on the underlying causes that explain such spreads. In most cases, default risk is used as a control variable and, therefore, the assessment of the default risk in green bonds can be considered a field of study with potential for improvement (Löffler et al. 2021).

Most recently, specifically after the signing of the Paris Agreement, some of the interest in the credit risk field has shifted from the green bond premium discussion to the firm-level analysis. This is because even if differences in bonds may be a primary source of analysis, transition risk is more closely related to emissions at the firm-level, since green bond labels are not associated with low carbon emissions at a company level (Ehlers et al. 2020).

Many analyses have focused on the development of a framework, built within the context of the IPCC objectives,[4] that is able to transpose the general equilibrium and macro-economic scenarios into profit and loss and balance sheet impacts, through the use of a driver that links the evolution of socio-economic and emissions factors to impacts on financial variables (UNEP FI 2018; Monnin 2018). Some simplified versions of these frameworks are based on sectoral shocks, considering a reduction of the equity value or cash flows in specific sectors, as presented in Battiston et al. (2017) and Vermeulen et al. (2018, 2021). These papers, while presenting non-homogeneous approaches with a low level of sophistication, still show that these combined fossil fuel exposures can also be amplified indirectly, by using shocks to asset values and GDP at the sectoral level.

Recently, supervisors have promoted more sophisticated approaches through the incorporation of innovations such as dynamic balance, which is required when events are considered over such a long time horizon; and by means of the use of macro–micro approaches, which combine climate scenarios affecting macro magnitudes with entity-level shocks (ECB 2021a).

Considering the results of these stress exercises, other authors suggest the importance of revising the current regulatory framework for the calculation of credit risk capital in the medium-term, both by proposing capital-based macroprudential policies

[4] Intergovernmental Panel on Climate Change.

to incorporate the climate dimension in the assessment of capital (ECB 2021b) and through climate-related additional capital requirements (ECB 2021c).

Other authors have taken advantage of new data sources and approaches, using more sophisticated hypotheses and models that relate climate behaviour to the performance of financial variables, within a context in which the paradigm has considerably shifted after the Paris Agreement.For instance, Clarkson et al. (2015) use a firm-level carbon emissions breakdown to assess the impact of these emissions on company value. The author found that investors consider not only the current amount of carbon emissions, but also the company's carbon efficiency compared to sectoral peers and the ability to pass on carbon costs to end consumers. In the same line, Jung et al. (2018) develop a carbon risk metric to assess the impact of carbon risk management on the cost of debt, defined using recent carbon emissions data and the CDP questionnaires. The results show that a firm's cost of debt will increase with its historical carbon risk profile but demonstrate that carbon-related risks awareness in CDP questionnaires will serve to mitigate the penalty.

Table 1 summarises the articles that link environment-related variables and credit risk and shows that, in general, recent papers concerning the environmental impact on credit risk synthesise the transition risk considering scope 1 and 2 carbon emissions, qualitative metrics or environmental scores. However, this limited definition is only appropriate for specific sectors or particular cases in which the main source of transition risk arises from such direct emissions, since it ignores the findings in Clarkson et al. (2015).

Additionally, in some cases, there are biases in the available emissions data. For example, in Safiullah et al. (2021) an initial dataset of 2500 firms was selected, but after filtering by the availability of carbon emissions information, only 574 companies were finally used.

Other authors rely on asset pricing theories to ensure the inclusion of certain differences in agents' preferences or the technology available. For example, in Daniel et al. (2016), a model that assumes that the atmosphere is an asset with negative payoffs and that includes uncertainty about CO_2 prices and climate change damage effects is resolved over time by discounting the impact of marginal benefits as a consequence of reducing emissions. Moreover, some authors consider that transition risk stems from the possibility of a significant amount of stranded assets due to changes in the market, regulatory environment or shifts in consumer preferences that directly affect companies' values. Accordingly, investors deduct the negative impact of this risk by considering the available information when deciding on their actions. Different authors have reached this conclusion through the analysis of differences in portfolio betas (Monasterolo & de Angelis 2020; Ramelli et al. 2018; Wagner et al. 2018). In the same vein, in Görgen et al. (2019) and Roncalli et al. (2021), a new Brown-Minus-Green factor[5] is followed to explain the differences in expected returns. In Görgen et al. (2019) a composite indicator, considering (i) current emissions, (ii) public perception of emissions and iii) companies' mitigation strategies, is used. Since this composite index uses several variables and may be difficult to reproduce, Roncalli et al. (2021)

[5] The BMG factor refers to the differences in returns in a portfolio between companies or investments classified as brown and those classified as green.

propose two carbon intensity alternatives based on the three scopes defined by both the GHG protocol and the MSCI carbon emissions exposure score.[6] The findings obtained in both cases indicate that carbon intensity is not the only factor that the market considers in relation to climate transition risk.

Therefore, we can conclude that different methods are used nowadays in both academia and industry to measure the transition risk depending on various additional factors, such as companies' carbon efficiencies compared to their sectoral peers, the ability to pass on carbon costs to end consumers and awareness of carbon-related risks in general terms.

3 Methodological framework

When assessing the impact of a climate risk factor on credit risk measurement, some assumptions that affect the following elements must be considered:

1. The definition of default, for which Merton's distance to default is used.
2. The climate risk factor, for which a dichotomous variable based on the Climate Change Commercial Risks Opportunities label is used.
3. The functional form of the relationship between the default and climate factors, as well as the control variables are used (factorial model).

The assumptions discussed above are explained in more detail in the following subsections.

3.1 Distance to default

For the purposes of this study, and to define the credit risk of the companies studied, Merton's distance to default model (Merton 1974) is followed. Specifically, we collect the information from the CRI-RMI database in which the following formula is used for each company (Duan et al. 2012).

$$DtD = \left(\frac{\ln\left(\frac{A_t}{P_t}\right)}{\sigma_A \sqrt{T - t}} \right) \tag{1}$$

where A_t represents the value of the company's assets at fair value at time t, P_t represents the value of the company's liabilities at fair value at time t, σ_A represents asset volatility, T represents the time horizon and t refers to the period for each calculation.

This source has been already used for similar purposes recently (Loeffler 2021; Atif and Ali 2021).

[6] This score measures the emission intensity of companies based on their efficiency considering the unit of sales MSCI (2020).

3.2 Transition climate risk definition

Due to the challenges of obtaining accurate information about emissions from a large number of companies, as well as the differences between transition risk and a company's carbon emissions, it was decided to use a qualitative label that will help to determine whether or not a certain firm is vulnerable to climate-related issues.

The proposed factor is the Climate Change Commercial Risks Opportunities indicator, retrieved from Eikon Refinitiv, which is defined as the 'development of new products/services to overcome the threats of climate change to the existing business model of the company—some companies take climate change as a business opportunity and develop new products/services' by Refinitiv.

3.3 Factorial model

Since the objective of this paper is to assess whether any climate-related factors have an influence on the distance to default, different variations on a baseline model are analysed to systematically assess the different functional ways in which a climate factor may affect distance to default for companies.

For this purpose, we estimate a base model to predict the distance to default differences by running the following regression:

$$\begin{aligned}\Delta DtD_{it} &= \alpha_i + \beta_1 \Delta SMB_{it} + \beta_2 \Delta PROF_{it} + \beta_3 \Delta LEV_{it} \\ &\quad + \beta_5 \Delta MARGIN_{it} + \beta_6 \Delta EAR_{it} + \gamma Y_{it} + \varepsilon_{it} \qquad (2)\end{aligned}$$

where

- DtD_{it} represents the distance to default for each company in each observed time period.
- SMB_{it} represents the size factor, calculated as the difference in the average distance to default between companies classified as big versus those classified as small.
- $PROF_{it}$ represents the profitability factor, calculated as the difference in the average distance to default between companies and the least profitable ones.
- LEV_{it} represents the leverage factor, calculated as the difference in the average distance to default between the most and least leveraged companies.
- $MARGIN_{it}$ represents the net margin factor, calculated as the difference in the average distance to default between companies with a higher net margin compared to those with the lowest net margin relative to assets.
- EAR_{it} represents the cumulative capital reserve factor, calculated as the difference in the average distance to default of companies with a higher positive change in reserves versus those with a lower change.
- Y_{it}. represents country and sectoral factors.
- ε_{it} represents the residual, considered to be a random time series with independent and identically distributed random variables (i.i.d.), uncorrelated with the explanatory variables and where $E(\varepsilon_{i,t}) = 0$.

These factor variables used as control variables are commonly employed in the academic literature as factors that affect the distance to default, for example, leverage in Zmijewski (1984), industry effects in Longstaff and Schwartz (1995), profitability in Tudela and Young (2003) and liquidity in Zeitun and Tian (2007).

3.4 Climate transition risk hypotheses

There is a great variety of approaches in the academic literature on how to generate climate factors. As discussed in Sect. 2, many studies incorporate firms' direct emissions as an explanatory factor for distance to default (Capasso et al. 2020; Safiullah et al. 2021; Kabir et al. 2021). Some authors have also pointed out that other variables are relevant even when sector is used as a control variable, such as public perception, mitigation capacity, available technology and differences in regulatory environment (Daniel et al. 2016; Görgen et al. 2019; Roncalli et al. 2021).

Alternatively, as mentioned in Sect. 2, in the field of asset pricing, the most common approach is the evaluation of differences in risk-adjusted returns that can be explained by climate factors. Similarly, this paper assesses if the grouping of companies according to climate-related criteria can be used to explain the evolution of changes in credit risk.

Hence, by using the distance to default obtained according to Merton's method as the dependent variable, the following three hypotheses to capture the climate risk factor are proposed:

Hypothesis 1 (H1) After the Paris Agreement, companies considered to be carbon intensive present a negative shift, compared to non-carbon intensive companies, in terms of distances to default in comparison to the time period prior to the signing of the Agreement.

This first hypothesis presumes that the signing of the Paris Agreement implies a shock to distance to default, so agents include companies' climate-related expectations in their valuation from that moment onwards.

Considering Eq. (2), the model has been adapted as follows:

$$\begin{aligned}\Delta DtD_{it} = {} & \alpha_i + \beta_1 \Delta SMB_{it} + \beta_2 \Delta PROF_{it} + \beta_3 \Delta LEV_{it} \\ & + \beta_5 \Delta MARGIN_{it} + \beta_6 \Delta EAR_{it} + \gamma Y_{it} + \varsigma_i PA_t + \varepsilon_{it}\end{aligned} \tag{3}$$

where *PA* represents a dichotomous variable that takes the value 1 if the time is after the signing of the Paris Agreement, and 0 otherwise.

Hypothesis 2 (H2) After the Paris Agreement, due to a change in the financial and sectoral coefficients, companies considered to be carbon intensive have smaller distances to default, compared to non-carbon intensity companies, than in the time period prior to the signing of the Agreement.

Secondly, the existence of any change in the parameters of the factorial model is evaluated. Namely, an assessment is made of whether the inclusion of interaction variables represents any difference in the coefficients of the variables included in the model, in comparison to the ones for the previous period.

Considering Eq. (2), the econometric model has been adapted as follows:

$$\begin{aligned}\Delta DtD_{it} \\ &= \alpha_i \\ &\quad + (\beta_1 \Delta SMB_{it} + \beta_2 \Delta PROF_{it} + \beta_3 \Delta LEV_{it} + \beta_5 \Delta MARGIN_{it} + \beta_6 \Delta EAR_{it}) \\ &\quad * \varsigma_i PA_t + \gamma Y_{it} + \varepsilon_{it}.\end{aligned} \tag{4}$$

Hypothesis 3 (H3) After the Paris Agreement, companies considered to be carbon intensive present smaller distances to default than non-carbon intensity companies, in comparison to the period prior to the signing of the Agreement, due to a new factor related to a specific climate factor.

Finally, it is evaluated whether an additional factor, calculated as the difference in the average distances to default for companies considered to be carbon intensive with respect to those that are not, is relevant after the Paris Agreement.

Considering Eq. (2), the econometric model has been adapted as follows:

$$\begin{aligned}\Delta DtD_{it} = \alpha_i + \beta_1 \Delta SMB_{it} + \beta_2 \Delta PROF_{it} + \beta_3 \Delta LEV_{it} \\ + \beta_5 \Delta MARGIN_{it} + \beta_6 \Delta EAR_{it} + \gamma Y_{it} + \beta_7 BMG_{it} * PA_t + \varepsilon_{it}\end{aligned} \tag{5}$$

where BMG_t represents the climate factor, calculated as the difference in the average distance to default among companies classified as affected by climate change risk and opportunities compared to those without this label.

4 Data and results

4.1 Data

To analyse the theoretical framework developed in the previous section, this assessment uses a sample with financial information from the companies that comprise the STOXX Europe 600. Samples run from 31 January 2010 to 31 December 2020. Data were extracted from Refinitiv in March 2022.

For some entities, financial or ESG information was not available at the time of data extraction. Additionally, companies that had recently been listed were removed due to lack of enough data. Table 2 presents summary statistics for the climate change risk label, default risk and financial factors. DtD refers to the Merton´s Distance to Default for each company in each period. SMB (Small minus Big), PROF (Profitability), LEV (Leverage), MARGIN (Net Margin), EAR_RET and CLIMATE (Climate Change Risk and Opportunities) refer, respectively, to the factor value for each period calculated as the difference in the average distance to default values for the group of companies for each week. It can be observed that all variables show a value with a mean equal to zero after the application of first differences. Also, similar standard deviation values are observed for the factors and relatively higher for DtD and CLIMATE.

Table 2 Descriptive statistics

Variables	*N*	Mean	St. Dev	Min	Max
Year	65,744			2010	2020
Market_DtD	65,744	– 0.001	0.094	– 1.543	1.297
SMB_FACTOR	65,744	0.0001	0.018	– 0.076	0.085
PROF_FACTOR	65,744	– 0.0005	0.028	– 0.107	0.121
LEV_FACTOR	65,744	– 0.00005	0.014	– 0.061	0.108
Net_Margin_FACTOR	65,744	– 0.001	0.017	– 0.112	0.064
Ear_Retained_FACTOR	65,744	– 0.0004	0.013	– 0.051	0.086
Climate_FACTOR	65,744	– 0.008	0.107	– 0.798	0.758
Paris	65,744	0.484	0.5	0	1

Note: All factor variables are calculated as weekly differences of the average distance to default values between the separate groups of companies for each factor. Paris represents a dummy variable which takes value 0 before the Paris Agreement and value 1 after it

For the labelling of the companies, this paper uses the information available in the company register ESG information in Refinitiv in March 2022, following the rationale presented in Sect. 3.2. In Table 3, it is observed that the climate label is positive in half of the companies, except for sectors such as energy and utilities, where most companies are identified as being subject to climate risk.

Merton's distance to default information was retrieved from the Credit Research Initiative (CRI) platform of the National University of Singapore, also in March 2022.

Finally, regarding frequency, a monthly basis was used for the calculation of both the factors of the model and the distance to default. This was due to the frequency base criteria from Merton's Distance to Default source (Fig. 1).

A first analysis shows that while the evolution of market capitalisation-weighted average distances to default present similar trends, periods with persistent differences also exist. Section 4.3 analyses these differences using a statistical model to assess whether these differences are significant and whether differences exist before and after the Paris Agreement.

4.2 Modelling decisions and assumptions

To carry out this analysis, a panel data approach with random effects through an estimation based on the calculation of a robust covariance matrix through cluster-robust standard errors was used. This panel data estimation approach has been used to avoid endogeneity-related problems that may arise with cross-sectional data, caused by the existence of relevant unobservable variables (Greene 2012). The suitability of this approach has been verified using the Breusch-Pagan Lagrange multiplier (Breusch and Pagan 1980) to prove the absence of heteroscedasticity.

The purpose of this analysis is to assess the immediate effects of a climatic event, considering any external variables that may be impacting the result. Therefore, it is determined that using the first differences approach to define the function is the most

Table 3 Climate risk label distribution

Sector	Paris	Climate risk label	Total	(%)
Communication services	0	996	1969	50.58
Communication services	1	828	1803	45.92
Consumer discretionary	0	2554	4210	60.67
Consumer discretionary	1	2382	4110	57.96
Consumer staples	0	2070	3190	64.89
Consumer staples	1	1924	2814	68.37
Energy	0	924	1152	80.21
Energy	1	816	960	85.00
Financials	0	3003	5029	59.71
Financials	1	3033	4951	61.26
Health care	0	1128	3244	34.77
Health care	1	1293	2890	44.74
Industrials	0	3176	5791	54.84
Industrials	1	3131	5448	57.47
Information technology	0	516	1868	27.62
Information technology	1	813	2013	40.39
Materials	0	2259	3544	63.74
Materials	1	2021	3158	64.00
Real estate	0	660	1990	33.17
Real estate	1	1023	2034	50.29
Utilities	0	1860	1872	99.36
Utilities	1	1600	1704	93.90
Communication services	0	996	1969	50.58
Communication services	1	828	1803	45.92

Note: The Paris column indicates whether the data refers to periods before or after the Paris Agreement, respectively corresponding to 0 and 1

suitable option for this particular study, as it allows us to evaluate the short-term changes in the variables rather than their long-term relationship.

In either case, for some variables, considered in levels, it has not been possible to reject the null hypothesis of no unit roots (see Table 4). It has also been verified that the same null hypothesis is not rejected for the case of first differences. For this purpose, the Maddala-Wu Unit-Root Test (Maddala and Wu 1999) has been used.

4.3 Results

The correlation between factors has been analysed to avoid multicollinearity issues. This is shown in Table 5.

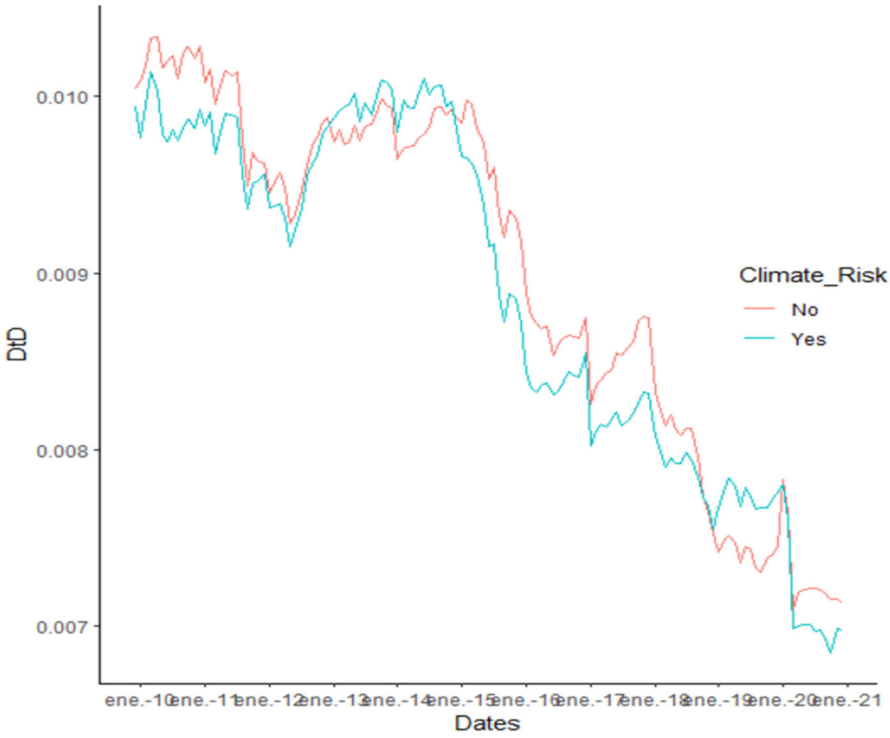

Fig. 1 Distance to Default by Climate label (Weighted average market capitalisation). Note: Figure shows distance to default for each group according to the climate label between 2010 and 2020 as a market capitalisation weighted average

Table 4 Panel unit root test of Maddala–Wu

Variables	Test statistic at level	Test statistics at difference
DtD	641.88	51,083***
SMB	788.31	57,472***
PROF	468.68	56,454***
LEV	1721.7***	56,968***
MARGIN	488.14	48,243***
EAR_RET	2555.5***	47,761***
CLIMATE	275.8	57,234***

***Means significant at the 1% level

There does not appear to be a strong ex-ante relationship between the variables, so no variable is excluded a priori. However, an ex-post test has been carried out to confirm that there are no issues with multicollinearity in any of the models.

Table 5 Correlation between explanatory variables

	SMB	PROF	LEV	MARGIN	EAR_RET	CLIMATE	Paris
SMB	1.000	– 0.653	0.214	– 0.259	– 0.094	0.226	– 0.086
PROF	– 0.653	1.000	– 0.159	0.676	0.029	– 0.122	0.049
LEV	0.214	– 0.159	1.000	0.057	– 0.136	0.023	– 0.012
MARGIN	– 0.259	0.676	0.057	1.000	– 0.192	0.194	0.086
EAR_RET	– 0.094	0.029	– 0.136	– 0.192	1.000	– 0.217	0.072
CLIMATE	0.226	– 0.122	0.023	0.194	– 0.217	1.000	– 0.096
Paris	– 0.086	0.049	– 0.012	0.086	0.072	– 0.096	1.000

Hypothesis 1 The results of the H1 model [Eq. (3)] are set out in Table 6. These indicate that significant differences between the distance to default exist before and after the Paris Agreement.

The relative importance of the different variables has been assessed following the approach used in Grömping (2007), through a variance decomposition-based method to allow for the calculation of importance for each variable. The results show that there is a systematic difference in the variations of the distances to default of the index evaluated before and after the Paris Agreement and that these differences are higher in magnitude than those explained by variables such as MARGIN and LEV, as it is shown in Table 7.

This finding is in keeping with the conclusions drawn from Monasterolo and de Angelis (2020) on how investors, after the signing of the Paris Agreement, are considering the differences between low-carbon and carbon-intensive companies in their investment decisions. This is also in keeping with Capasso et al. (2020) and Kabir et al. (2021) in terms of how this impact can be observed as differences in the credit risk for intensive carbon emission companies compared to those with lower emission volumes.

Hypothesis 2 In this case, the aim is to assess if the distance to default differences observed can be captured through classical financial variables as set out in H2. The underlying hypothesis is that even when there are differences in transition risk, this does not affect distance to default as a direct factor, but rather it influences the various financial variables and, subsequently, distance to default.

To assess this hypothesis, the starting point is the previous model, but incorporating the Paris Agreement dummy variable as an interaction variable with the financial variables.

As can be seen in Table 8, although the coefficients of the classical financial variables have changed after the Paris Agreement, the impact of the Paris Agreement on the distance to default is still present. This finding is in keeping with the conclusions drawn from Capasso et al. (2020), Safiullah et al. (2021) and Kabir et al. (2021), whose work explicitly includes factors that measure exposure to climate risk through emissions, in addition to the classical financial factors.

Table 6 Results of Eq. (3) assessing Hypothesis 1: linear panel regression of distance to default differences before and after the Paris Agreement

	Distance-to-default (first differences) *Dependent variable*			
	Fixed effects		Random effects	
	(1)	(2)	(3)	(4)
SMB	− 0.114*** (0.007)	− 0.119*** (0.007)	− 0.114*** (0.007)	− 0.119*** (0.007)
PROF	0.078*** (0.009)	0.072*** (0.009)	0.078*** (0.009)	0.071*** (0.009)
LEV	0.032*** (0.004)	0.031*** (0.004)	0.031*** (0.004)	0.031*** (0.004)
MARGIN	0.027*** (0.007)	0.034*** (0.007)	0.026*** (0.007)	0.034*** (0.007)
EAR_RET	− 0.106***(0.05)	− 0.102*** (0.005)	− 0.106*** (0.05)	− 0.102*** (0.005)
Paris		− 0.076*** (0.005)		− 0.083*** (0.003)
Constant			0.000 (0.002)	0.040*** (0.003)
Industry controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Observations	65,744	65,744	65,744	65,744
Adjusted R^2	0.037	0.038	0.045	0.047
F Statistic	617.268***	530.376***	3,097.896***	3,219.454***

Standard deviation in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Robust standard errors in parentheses. Standardised coefficients. In the case of models 1 and 3, model 3 (fixed effects) is preferred according to the Hausman test (Hausman 1978); chi-square:7.2724, p value: 0.2012. In the case of models 2 and 4, model 4 is preferred (fixed effects) according to the Hausman test; chi-square: 14.353, p value: 0.0259

Table 7 Relative importance by variable in Hypothesis 1

Variable	Importance	Standard deviation
SMB	0.0251	0.000656
EAR_RET	0.0184	0.000598
PROF	0.00966	0.000542
Paris	0.00332	0.000299
MARGIN	0.00238	0.000288
LEV	0.00198	0.000229

Note: The importance for each variable refers to the marginal variable importance in the R2 decomposition for random forest estimation. Standard deviation refers to standard deviation in the importance considering 1000 bootstrapping simulation

Table 8 Results of Eq. (4) assessing Hypothesis 2: linear panel regression of distance to default with interaction variables before and after the Paris Agreement

	Distance-to-default (first differences) *Dependent variable*	
	Fixed effects	Random effects
	(1)	(2)
SMB	– 0.204*** (0.008)	– 0.204*** (0.008)
PROF	– 0.158*** (0.012)	– 0.158*** (0.012)
LEV	0.020*** (0.005)	0.020*** (0.005)
MARGIN	0.158*** (0.011)	0.158*** (0.011)
EAR_RET	– 0.75*** (0.007)	– 0.75*** (0.007)
Paris	– 0.077*** (0.005)	– 0.084*** (0.005)
SMB*Paris	0.215*** (0.012)	0.215*** (0.012)
PROF*Paris	0.431*** (0.017)	0.431*** (0.017)
LEV*Paris	– 0.026*** (0.008)	– 0.027*** (0.008)
MARGIN*Paris	– 0.174*** (0.012)	– 0.173*** (0.012)
EAR_RET	– 0.062*** (0.008)	– 0.061*** (0.008)
Constant		0.048*** (0.003)
Industry controls	Yes	Yes
Country controls	Yes	Yes
Observations	65,744	65,744
Adjusted R^2	0.052	0.060
F Statistic	380.691***	4,230.209***

Standard deviation in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Robust standard errors in parentheses. Standardised coefficients. In the case of models 1 and 2, model 2 is preferred (fixed effects) according to the Hausman test; chi-square:14.709, p value: 0.196

Hypothesis 3 Finally, following the methodology used by Görgen et al. (2019) and Roncalli et al. (2021), a dichotomous climate risk variable is included in the model in H3.

As shown in Table 9, in the same way as for the other hypotheses, different model specifications are proposed to assess this assumption. For models 2 and 4, a climate factor is included, calculated as stated in Hypothesis 3 (Table 10).

Again, it can be seen that the climate variable is relevant and has a similar weight to the Paris Agreement. Nevertheless, the interaction variable has limited weight in the model. Thus, while the climate factor is relevant, it does not seem that the Paris Agreement has caused it to become more influential or has had a significant impact on it since its inception. In Table 10, it can be seen that Paris dummy and climate factor have similar importance and it is higher than other classical financial variables such as leverage or margin. Despite the statistical significance of the climate factor after the Paris agreement, it becomes apparent that importance in the model is limited. This finding extends Capasso et al. (2020) to the periods before the Paris Agreement and is in line with the findings of Kabir et al. (2021) and Safiullah et al. (2021).

Table 9 Results of Eq. (5) assessing Hypothesis 3: linear panel regression of distance to default differences with Climate Risk factor

	Distance-to-default (first differences) *Dependent variable*			
	Fixed effects		Random effects	
	(1)	(2)	(3)	(4)
SMB	− 0.098*** (0.007)	− 0.102*** (0.007)	− 0.098*** (0.007)	− 0.102*** (0.007)
PROF	0.088*** (0.009)	0.084*** (0.009)	0.089*** (0.009)	0.084*** (0.009)
LEV	0.036*** (0.005)	0.038*** (0.005)	0.036*** (0.005)	0.037*** (0.005)
MARGIN	0.023*** (0.007)	0.031*** (0.007)	0.022*** (0.007)	0.031*** (0.007)
EAR_RET	− 0.108*** (0.005)	− 0.103*** (0.005)	− 0.108*** (0.005)	− 0.103*** (0.005)
CLIMATE	− 0.029*** (0.005)	− 0.040*** (0.007)	− 0.029*** (0.005)	− 0.040*** (0.007)
Paris		− 0.078*** (0.005)		− 0.085*** (0.005)
CLIMATE*Paris		0.018** (0.009)		0.017** (0.009)
Constant			− 0.001 (0.002)	0.041*** (0.003)
Industry Controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Observations	65,744	67,313	67,313	67,313
Adjusted R^2	0.038	0.039	0.046	0.047
F Statistic	522.099***	404.740***	3,145.600***	3,276.345***

Standard deviation in parentheses. $*p<0.1$; $**p<0.05$; $***p<0.01$. Robust standard errors in parentheses. Standardised coefficients. In the case of models 1 and 3, model 3 (fixed effects) is preferred according to the Hausman test (Hausman 1978); chi-square:7.9611, p value: 0.241. In the case of models 2 and 4, model 4 is preferred (fixed effects) according to the Hausman test; chi-square: 16.331, p value: 0.03788

5 Conclusions

Interest in analysing the climate dimension of risk has grown recently in both the financial and academic fields. This attention is particularly focused on understanding the impact of the climate dimension on investors' perceptions of risk and how this risk translates into specific metrics, in terms of both financial performance and financial risks.

This paper extends the current credit risk-focused analyses by assessing whether market perception can be evaluated to measure the credit risk that investors discount

Table 10 Relative importance by variable in Hypothesis 3

Variable	Importance	Standard deviation
SMB	0.0201	0.000678
EAR_RET	0.0188	0.000646
PROF	0.014	0.000649
Paris	0.00352	0.000313
CLIMATE	0.00313	0.000297
LEV	0.00265	0.000267
MARGIN	0.00184	0.000259
CLIMATE*Paris	0.00028	9.09E-05

Note: The importance for each variable refers to the marginal variable importance in the R2 decomposition for random forest estimation. Standard deviation refers to standard deviation in the importance considering 1000 bootstrapping simulation

in the market. It provides empirical evidence on the relationship between a climate factor after the Paris Agreement and the distance to default.

Considering the results of the three stated hypotheses, the first conclusion is that investors consider transition risk, and this can be linked to differences in credit risk. The second conclusion is that these differences cannot be captured by classical financial indicators. Although there is substantial evidence in the academic literature about the impact of emission behaviour on financial performance, climate transition risk is beyond this relationship, requiring additional variables to measure its impact.

The main conclusion is that since transition risk scenarios are known and can be discounted by the markets, they may be observable in the implicit market default rate. Therefore, this approach could be useful as a method to incorporate transition risk-related market expectations. This would involve adapting transition default rate determination to include the effects of the value chain or the technological capacity to reduce or mitigate emissions under a transition scenario, possible differences in regulatory frameworks and consumer responses. Moreover, the more the regulation is acknowledged, the fewer transition scenarios there are and the easier it is to assign a probability of occurrence to them. Consequently, markets will be more capable of discounting the effects on the value of companies.

Finally, some elements can only be incorporated through market-based variables or scenarios, particularly those related to the existence of less polluting technological alternatives as well as those whose origin is reputational or market-based, even when some assumptions regarding the absence of mispricing and symmetrical information are necessary.

In view of the above, expanded emissions-based approaches with variables that capture consumer and market preferences, as well as differences in regulatory frameworks, do not address all the limitations of emission factoring approaches but provide some improvements that can be incorporated into existing frameworks.

However, several challenges still remain in terms of both data availability and methodological refinement. In relation to data, one of the main issues is the lack of standardisation between "green" and "brown" companies and also the broad definition of climate risk and the multiple channels through which it affects credit risk. This is one of the most important limitations in the comparison of results or the standardisation of analyses, along with the availability of databases, including scope 1, 2 and 3 emissions for a larger set of companies and having consistent calculations across sectors and over time.

In terms of the methodology, additional refinements are required. Examples of such challenges are a more sophisticated consideration of the impact of regulatory framework changes over time, for example by assigning a different timing of impacts after the Paris Agreement depending on the sector, relaxing the assumptions regarding market efficiency and a joint analysis of market and emissions variables.

Funding The work was supported by Universidad Nacional de Educación a Distancia (UNED) [076-044355 ENER-UK] and the Spanish Ministry of Science and Innovation [PID2020-113367RBI00]. Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature.

Declarations

Conflict of interest Authors declare that they do not have financial or non-financial interests that are directly or indirectly related to this work submitted for publication.

Consent for publication The manuscript has not been submitted to more than one journal for simultaneous consideration. The submitted work is original and does not have been published elsewhere in any form or language (partially or in full).

References

Agliardi E, Agliardi R (2019) Financing environmentally-sustainable projects with green bonds. Environ Dev Econ 24(6):608–623. https://doi.org/10.1017/S1355770X19000020

Atif M, Ali S (2021) Environmental, social and governance disclosure and default risk. Bus Strateg Environ 30(8):3937–3959. https://doi.org/10.1002/bse.2850

Baker M, Bergstresser D, Serafeim G, Wurgler J (2022) Financing the response to climate change: the pricing and ownership of U.S. Green bonds. Annu Rev Financial Econ 14:415–437. https://doi.org/10.1146/annurev-financial-111620-014802

Battiston S, Mandel A, Monasterolo I, Schütze F, Visentin G (2017) A climate stress-test of the financial system. Nat Clim Chang 7(4):283–288. https://doi.org/10.1038/nclimate3255

Bauer R, Hann D (2010) Corporate environmental management and credit risk. *Working Paper. Maastricht University. European Centre for Corporate Engagement (ECCE)*. https://doi.org/10.2139/ssrn.1660470

BCBS (Basel Committee on Banking Supervision) (2020) Climate-related financial risks: a survey on current initiatives. Bank for International Settlements, April. Retrieved from https://www.bis.org/bcbs/publ/d502.pdf

BCBS (Basel Committee on Banking Supervision (2021a) Climate-related financial risks-measurement methodologies. Bank for International Settlements, April. Retrieved from https://www.bis.org/bcbs/publ/d518.pdf

BCBS (Basel Committee on Banking Supervision (2021b) Climate-related risks drivers and their transmission channels. Bank for International Settlements, April. Retrieved from https://www.bis.org/bcbs/publ/d517.pdf

Breusch TS, Pagan AR (1980) The lagrange multiplier test and its applications to model specification in econometrics. Rev Econ Stud 47(1):239–253. https://doi.org/10.2307/2297111

Capasso G, Gianfrate G, Spinelli M (2020) Climate change and credit risk. J Clean Prod 266:121634. https://doi.org/10.1016/j.jclepro.2020.121634

Chava S (2014) Environmental externalities and cost of capital. Manage Sci 60(9):2223–2247. https://doi.org/10.1287/mnsc.2013.1863

Clarkson PM, Li Y, Pinnuck M, Richardson GD (2015) The valuation relevance of greenhouse gas emissions under the european union carbon emissions trading scheme. Eur Account Rev 24(3):551–580. https://doi.org/10.1080/09638180.2014.927782

Daniel KD, Litterman RB, Wagner G (2016) Applying asset pricing theory to calibrate the price of climate Risk. *NBER Working Papers,* Retrieved from https://ideas.repec.org/p/nbr/nberwo/22795.html

Drago D, Carnevale C, Gallo R (2019) Do corporate social responsibility ratings affect credit default swap spreads? Corp Soc Responsib Environ Manag 26:644–652. https://doi.org/10.1002/csr.1709

Duan J, Sun J, Wang T (2012) Multiperiod corporate default prediction—A forward intensity approach. J Econom 170(1):191–209. https://doi.org/10.1016/j.jeconom.2012.05.002

ECB (European Central Bank) (2020) *Guide on climate-related and environmental risks*. European Central Bank, November. Retrieved from https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.202011finalguideonclimate-relatedandenvironmentalrisks~58213f6564.en.pdf

ECB (European Central Bank) (2021a) Towards a macroprudential stress test and growth-at-risk perspective for climate-related risk. *ECB Macroprudential Bulletin*, October, issue 15. Retrieved from https://www.ecb.europa.eu/pub/financial-stability/macroprudential-bulletin/focus/2021a/html/ecb.mpbu_focus202110_1.en.html

ECB (European Central Bank) (2021b) The challenge of capturing climate risks in the banking regulatory framework: is there a need for a macroprudential response? *ECB Macroprudential Bulletin*, October, Issue 15. Retrieved from https://www.ecb.europa.eu/pub/financial-stability/macroprudential-bulletin/html/ecb.mpbu2021b10_1~5323a5baa8.en.html

ECB (European Central Bank) (2021c) A theoretical case for incorporating climate risk into the prudential framework. *ECB Macroprudential Bulletin*, October, issue 15. Retrieved from https://www.ecb.europa.eu/pub/financial-stability/macroprudential-bulletin/focus/2021c/html/ecb.mpbu_focus2021c10_2.en.html

Ehlers T, Packer F (2017) Green Bond Finance and Certification. *BIS Quart Rev* September, 89–104

Ehlers T, Mojon B, Packer F (2020) Green bonds and carbon emissions: exploring the case for a rating system at the firm level. *BIS Quart Rev* September, 31–47

Ehlers T, Packer F, de Greiff K (2021) The pricing of carbon risk in syndicated loans: Which risks are priced and why? J Bank Finance 2021:106180. https://doi.org/10.1016/j.jbankfin.2021.106180

Feridun M, Güngör H (2020) Climate-related prudential risks in the banking sector: a review of the emerging regulatory and supervisory practices. Sustainability 12(13):5325. https://doi.org/10.3390/su12135325

Görgen M, Jacob A, Nerlinger M, Riordan R, Rohleder M, Wilkens M (2019) Carbon risk. Unpublished working Paper. University of Augsburg. Retrieved from https://doi.org/10.2139/ssrn.2930897

Greene WH (2012) 11. Models for panel data in econometric analysis, 7th ed. Pearson Education, Inc, New York, pp 383–471

Grömping U (2007) Estimators of relative importance in linear regression based on variance decomposition. Am Stat 61:139–147. https://doi.org/10.1198/000313007X188252

Hachenberg B, Schiereck D (2018) Are green bonds priced differently from conventional bonds? J Asset Manag 19(6):371–383. https://doi.org/10.1057/s41260-018-0088-5

Harrison C (2019) Green bond pricing in the primary market: January–June 2019. Retrieved from https://www.climatebonds.net/resources/reports/green-bond-pricing-primary-market-h1-2021

Hausman JA (1978) Specification test in econometrics. Econometrica 46:1251–1271. https://doi.org/10.2307/1913827

International Energy Agency. (2020) Global Energy Review 2020 – Analysis and key findings. A report by the International Energy Agency. Retrieved from https://www.iea.org/reports/global-energy-review-2020

Jung J, Herbohn K, Clarkson P (2018) Carbon risk, carbon risk awareness and the cost of debt financing. J Bus Ethics 150(4):1151–1171. https://doi.org/10.1007/s10551-016-3207-6

Kabir MN, Rahman S, Rahman MA, Anwar M (2021) Carbon emissions and default risk: international evidence from firm-level data. Econ Modell 103:105617. https://doi.org/10.1016/j.econmod.2021.105617

Löffler KU, Petreski A, Stephan A (2021) Drivers of green bond issuance and new evidence on the "greenium." Eurasian Econ Rev 11(1):1–24. https://doi.org/10.1007/s40822-020-00165-y

Longstaff FA, Schwartz ES (1995) A simple approach to valuing risky fixed and floating rate debt. J Financ 50(3):789–819. https://doi.org/10.1111/j.1540-6261.1995.tb04037.x

MacAskill S, Roca E, Liu B, Stewart R, Sahin O (2021) Is there a green premium in the Green Bond market? Systematic literature review revealing premium determinants. J Clean Prod 280:124491. https://doi.org/10.1016/j.jclepro.2020.124491

Maddala GS, Wu S (1999) A comparative study of unit root tests with panel data and a new simple test. Oxf Bull Econ Stat 61(9):631–652. https://doi.org/10.1111/1468-0084.0610s1631

Mardani A, Streimikiene D, Cavallaro F, Loganathan N, Khoshnoudi M (2019) Carbon dioxide (CO_2) emissions and economic growth: a systematic review of two decades of research from 1995 to 2017. Sci Total Environ 649:31–49. https://doi.org/10.1016/j.scitotenv.2018.08.229

Merton RC (1974) On the pricing of corporate debt: the risk structure of interest rates. J Finance 29:449–470. https://doi.org/10.2307/2978814

Monasterolo I, de Angelis L (2020) Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. Ecol Econ 170:106571. https://doi.org/10.1016/j.ecolecon.2019.106571

Monnin P (2018) Integrating climate risks into credit risk assessment: current methodologies and the case of central banks corporate bond purchases. Counc Econ Polic. https://doi.org/10.2139/ssrn.3350918

MSCI (2020) *MSCI ESG Ratings Methodology*. MSCI ESG Research. Retrieved from https://www.msci.com/documents/10199/1283513/MSCI_ESG_Metrics_Calc_Methodology_Dec2020.pdf/92a299cb-0dbc-63ba-debb-e821bd2e2b08

Nandy M, Lodh S (2012) Do banks value the eco-friendliness of firms in their corporate lending decision? Some empirical evidence. Int Rev Financ Anal 25(1):83–93. https://doi.org/10.1016/j.irfa.2012.06.008

NGFS (Network for Greening the Financial System) (2017) Joint statement by the founding members of the central banks and supervisors network for greening the financial system – one planet summit. *Network for Greening the Financial System,* Retrieved from https://www.ngfs.net/en/communique-de-presse/joint-statement-founding-members-central-banks-and-supervisors-network-greening-financial-system-one-0

NGFS (Network for Greening the Financial System) (2019) A call for action – Climate Change as a source of financial risk. Retrieved from https://www.banque-france.fr/en/financial-stability/international-role/network-greening-financial-system/first-ngfs-progress-report

Oikonomou I, Brooks C, Pavelin S (2014) The effects of corporate social performance on the cost of corporate debt and credit ratings. Financ Rev 49(1):49–75. https://doi.org/10.1111/fire.12025

Ramelli S, Wagner AF, Zeckhauser RJ, Ziegler A (2018) Stock price rewards to climate saints and sinners: evidence from the trump election. Swiss Finance Institute Research Paper Series, 18–63. Retrieved from https://ideas.repec.org/p/chf/rpseri/rp1863.html

Roncalli T, Le Guenedal T, Lepetit F, Roncalli T, Sekine T (2021) The market measure of carbon risk and its impact on the minimum variance portfolio. J Portf Manag 47(9):54–68. https://doi.org/10.3905/jpm.2021.1.285

Safiullah M, Kabir MN, Miah MD (2021) Carbon emissions and credit ratings. Energy Econ 100:105330. https://doi.org/10.1016/j.eneco.2021.105330

Sharfman MP, Fernando CS (2008) Environmental risk management and the cost of capital. Strateg Manag J 29(6):569–592. https://doi.org/10.1002/smj.678

Tang DY, Zhang Y (2020) Do shareholders benefit from green bonds? J Corp Finance 61:101427. https://doi.org/10.1016/j.jcorpfin.2018.12.001

Tudela M, Young G (2003) A Merton-model approach to assessing the default risk of UK public companies. Bank Engl Quart Bull 43(3):328

UNEP FI (United Nations Environment Programme-Finance Initiative) (2018) Extending our horizons: assessing credit risk and opportunity in a changing climate. United Nations Environment Programme-Finance Initiative. Retrieved from https://www.unepfi.org/news/themes/climate-change/extending-our-horizons/

UNEP FI (United Nations Environment Programme-Finance Initiative) (2019) Changing course: a comprehensive investor guide to scenario-based methods for climate risk assessment, in response to the TCFD. United Nations Environment Programme-Finance Initiative. Retrieved from https://www.unepfi.org/wordpress/wp-content/uploads/2019/05/TCFD-Changing-Course-Oct-19.pdf

UNFCCC (United Nations Framework Convention on Climate Change) (2016) Report of the conference of the parties on its twenty-first session, held in Paris from 30 November to 13 December 2015. Addendum. Part two: Action taken by the Conference of the Parties at its twenty-first session. Paris: United Nations Framework Convention on Climate Change. Retrieved from: https://unfccc.int/resource/docs/2015/cop21/eng/10a01.pdf

Vermeulen R, Schets E, Lohuis M, Kolbl B, Jansen D, Heeringa W (2018) An energy transition risk stress test for the financial system of the Netherlands. Netherlands Central Bank, Research Department. Retrieved from https://ideas.repec.org/p/dnb/dnbocs/1607.html

Vermeulen R, Schets E, Lohuis M, Kölbl B, Jansen D, Heeringa W (2021) The heat is on: a framework for measuring financial stress under disruptive energy transition scenarios. Ecol Econ 190:107205. https://doi.org/10.1016/j.ecolecon.2021.107205

Wagner AF, Zeckhauser RJ, Ziegler A (2018) Company stock price reactions to the 2016 election shock: trump, taxes, and trade. J Financ Econ 130(2):428–451. https://doi.org/10.1016/j.jfineco.2018.06.013

WRI (World Resources Institute) (2014) Greenhouse gas protocol: policy and action standard. *Washington: World Resources Institute.* Retrieved from https://ghgprotocol.org/sites/default/files/Guidance_Handbook_2019_FINAL.pdf

Zanin L (2022) Estimating the effects of ESG scores on corporate credit ratings using multivariate ordinal logit regression. Empir Econ. https://doi.org/10.1007/s00181-021-02121-4

Zeitun R, Tian G (2007) Capital structure and corporate performance: evidence from Jordan. Aust Account Bus Finance J 1(4):40–61. https://doi.org/10.14453/aabfj.v1i4.3

Zerbib OD (2019) The effect of pro-environmental preferences on bond prices: evidence from green bonds. J Bank Finance 98:39–60. https://doi.org/10.1016/j.jbankfin.2018.10.012

Zmijewski ME (1984) Methodological issues related to the estimation of financial distress prediction models. J Account Res 22(2):59–82. https://doi.org/10.2307/2490859