Department of Economics and Finance

Chair of Empirical Finance

The Impact of Climate Change on Credit Risk

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Contents

Introduction

Climate change is one of the most significant challenges facing humanity this century. The extent of the environmental impact of climate change is still uncertain, but recent scientific evidence is increasingly worrying and many governments are taking decisive action. A transition to a low-carbon economy is therefore unavoidable. A concrete approach to this change requires the activation of a wide range of financial instruments and innovations of various kinds that will have significant implications for all players in the economic scenario: markets, companies, intermediaries and investors. Climate change and global warming are addressed by stricter regulation by governments (e.g., carbon pricing mechanisms), new emerging technologies and changes in consumer behavior. For this reason, global investors are increasingly concerned about the implications of climate change, particularly on the pricing of financial assets and the allocation of their investment portfolios. There has even been speculation that exposure to climate risk could threaten global financial stability.

The most important and decisive climate agreement is undoubtedly the Paris Agreement, which has set ambitious goals: keeping the global average temperature increase well below 2°C and continuing action to limit this increase to 1.5°C compared to pre-industrial levels; increasing adaptive capacity to the adverse effects of climate change by promoting climate resilience and low greenhouse gas emission development; making financial flows consistent with a pathway towards low greenhouse gas emission and climate-resilient development. European countries and the United States have committed themselves to progressively reducing greenhouse gas emissions to achieve these goals. In addition, the European Union (EU), which is undoubtedly one of the most active players in this field, has also adopted ambitious legislation in various sectors by setting binding emission targets for critical sectors of the economy to reduce greenhouse gas emissions substantially. In line with the Paris Agreement, the EU has endorsed a net reduction in greenhouse gas emissions of at least 55% by 2030 compared to 1990 levels to achieve a climate-neutral EU by 2050. It will benefit people and the environment and limit global warming (Jäger-Waldau et al. (2020)). Therefore, it is clear that every company should strive to substantially reduce its greenhouse gas emissions out of respect for the planet and safeguard its long-term survival. Given the introduction of stricter policies to catalyze the transition to a low-carbon economy, companies that do not comply could attract punitive taxation; their financing costs could rise, thus reducing their ability to repay debts (Ersoy and Musluoglu (2021)). As a result, a company with a higher carbon footprint is more exposed to transition risk: it may have a higher credit risk both now and in the future, especially if it does not have a credible plan to transition to a low-carbon economy and fails to adapt promptly.

While the relationship between climate risk exposure and stock prices is receiving growing attention in the literature, the impact on corporate bonds appears relatively underexplored (Kleimeier and Viehs (2016)). Our work contributes to the existing literature by investigating the relationship between exposure to climate change and firm credit risk. For this purpose, we consider the constituents of the Eurostoxx 50 index, a market capitalization-weighted stock index designed to represent the 50 largest companies in the Eurozone, over the period 2007-2021. There are several different approaches to estimating credit risk. One of these is the Structural models in which the company's default depends on its financial and capital structure (e.g., Merton and Black & Cox models). In our paper, as a credit risk measure, we decided to use the Distance to Default computed according to the Black & Cox model, which considers the assumption that default can occur when the firm's value falls below a specific time-dependent barrier. On the other hand, Climate risk is measured as the amount of Greenhouse Gas (GHG) emissions in three different categories: Scope_1, i.e., direct emissions, Scope_2, i.e., indirect emissions from energy consumption, and Scope_3, i.e., all other indirect emissions caused by the entire value chain.

In our econometric framework, we partition the sample according to the company's level of emissions into non-homogeneous terciles. The descriptive statistics reveal the influence of GHG emissions on the distance to default: the firms in the first tercile (lesser emissions) have a higher distance to default than firms in the third tercile (higher emissions). Using a panel least squares regression was found a ceteris paribus, significant and negative relationship between the Black & Cox Distance to Default and the level of GHG emissions. Subsequently, through a difference-in-difference model, we consider the impact of the Paris Agreement as an exogenous policy shock attempt to ascribe greater causality to some of our findings, given the financial markets' concern about exposure to stricter climate policies. However, after the Paris agreement, high emitting companies significantly shortened their distance to default compared to low emitters. Despite this confirmation, we performed further investigations to avoid our results being driven by energy and extractive companies in the sample, endogeneity and serial correlation issues. Nevertheless, the results confirmed a significant and negative relationship between the distance to default and the level of GHG emissions.

The remainder of this paper is organized as follows: Chapter 1 reviews the central studies in literature based on the relationship between environmental and financial performance and the hypotheses to be tested; Chapter 2 focuses on the methodology to estimate credit risk, the range of quantitative metrics to quantify climate risk and the sample; Chapter 3 presents the empirical analysis which illustrates the relationship between Black & Cox Distance to Default and the level of GHG emissions; Chapter 4 discusses a methodological and empirical comparison between our econometric framework and the benchmark Capasso et al. (2020).

Chapter 1

Literature and Hypotheses

1.1 Literature

Public opinion, governments, business leaders and institutional investors worldwide have been awakened to the urgency of fighting for climate change. An increasing number of academic research studies are focusing on climate-related risks. Economic actors are increasingly aware that the consequences of climate change are upon us and represent a current and relevant danger to the global economy and the financial sector. As a result, more than 100 countries (accounting for almost 50% of the world's GDP) are committing to climate change targets (Kalesnik et al. (2021)).

Carney (2015) claims that climate change risk can impact financial stability in three different modes: physical risks, i.e., extreme weather and climate events that affect the value of financial assets; liability risks, arising from increased compensation paid to economic agents affected by climate change; transition risks, deriving from the adjustment of asset prices towards a low-carbon economy. The latter are materializing where new regulations creates obligations to move towards a lower-carbon economy, e.g., the imposition of a price on greenhouse gas emissions. This tendency brought to the fact that a growing number of countries are decreasing their emissions and maneuvering private investments into cleaner options (Bento and Gianfrate (2020); Aldy and Gianfrate (2019)). Therefore, all high-carbon assets could be subject to penalizing regulation, thus changing investors' perception of its future profitability and creditworthiness (Koten (2018)). So, investors are faced with the challenge of finding the best mode to consider climate risk in their investment decisions.

The increase in academic studies on the relationship between a company's sustainability and financial performance should provide sufficient insights into an excellent solution to this challenge. However, more than 85% of the studies investigating this relationship are related to equities, although bonds have a market share of almost 40% of sustainable investments in Europe (Gianfrate and Lorenzato (2018)). In detail, most academics have focused on the specific binding between climate-related transition risk and equity returns. This line of research establishes that equity market investors tend to demand higher returns from companies with higher levels of greenhouse gas emissions (Bolton and Kacperczyk (2020)).

Empirical research on the relationship between climate-related transition risk and credit risk is much more limited and most of it has only considered environmental scores provided by rating agencies or retrospective environmental metrics such as GHG emissions (Seltzer et al. (2022); Ginglinger and Moreau (2019)). This branch of literature detects that firms with higher GHG emissions or worse environmental scores have a higher credit risk measured by bond credit ratings, CDS spreads, or distance to default (Barth et al. (2022)). Stellner et al. (2015) empirically demonstrate how higher corporate social responsibility (CSR) performance translates into lower credit risk, as measured by zero-volatility spreads, the so-called z-spread. Attig et al. (2013) analyze the relationship between corporate ratings and ESG (Environmental Social Governance) scores, finding that a better environmental score is associated with a better rating. Höck et al. (2020) investigate how a company's environmental sustainability affects its credit risk premium, showing that companies with higher environmental sustainability have lower credit spreads. It is the first study to use credit default swap (CDS) spreads to measure credit risk and investigate the relationship between its environmental sustainability score and credit risk, covering all industries except financial. Bauer and Hann (2010) show that poor environmental performances are associated with worse credit ratings and higher spreads for corporate bonds. Safiullah et al. (2021) analyze how carbon emissions have a negative and economically significant impact on credit ratings in the US market. Although some of these studies take ESG ratings as a measure of environmental performance, there are important warnings about using these scores: they are often inconsistent over time and incomparable across companies and sectors, showing a very low correlation between different providers. Therefore, ESG scores may not be an adequate proxy for transition risk (Berg et al. (2019); Billio et al. (2022); Schnabel (2020)). GHG emissions are likely to be a better proxy. They can be effectively exploited under informed methodological choices that acknowledge and address caveats on the availability, reliability, and comparability of such data. (Busch et al. (2022); Radu et al. (2020); Breitenfellner et al. (2021)).

Similar to our study, Capasso et al. (2020) show the negative relationship between the Merton Distance to Default, a widely used market-based measure of firm credit risk, and the firm's carbon emissions. We contribute to the literature by investigating whether firm's climate-related risks, expressed as the level of GHG emissions (in the specification of $Scope_1$, $Scope_2$ and $Scope_3$), are associated with Black & Cox Distance to Default, a measure of creditworthiness.

1.2 Hypotheses

This paper explains how the need to transition to a low-carbon economy influences firm credit risk by looking in-depth at the relationship between a firm's exposure to climate risks and the distance to default. For this reason, the following two crucial variables are considered: the credit risk, measured through the distance to default computed according to the Black & Cox model; the carbon footprint, expressed with the natural logarithm of emissions.

Due to higher carbon taxes or more expensive carbon allowances in emissions trading schemes, companies with larger carbon footprints are more exposed to progressively stricter climate regulations. It implies that their future cash flow is more likely to be affected than companies with smaller carbon footprints. Companies with smaller expected cash earnings entail lower corporate asset values and, lesser perceived ability to repay debt, lower creditworthiness. In line with this, the following assumption is stated (Carbone et al. (2021)):

$H1$: There is a positive relationship between a firm's exposure to transition risk and credit risk.

Then we test the relationship between carbon footprint exposure and credit risk after an unexpected event on global climate policies, the Paris Agreement. After this event, the most ambitious and decisive climate agreement that brought an abrupt tightening of global climate policies, we expected that credit risk would increase for companies with higher emissions. The choice of December 2016 of the Paris Agreement as an unexpected turning point in global climate regulation is consistent with several contributions in the literature (pricing of climate policy risk) and its ratification date (4/11/2016). Our further hypothesis is:

H2. Firms with larger carbon footprints increase their credit risk more than firms with smaller carbon footprints following the Paris Agreement.

Chapter 2

Methodology

2.1 The Measure of Credit Risk

Credit risk is the possibility of a loss resulting from a borrower's failure to repay a loan or meet contractual obligations. The Basel Committee defines credit risk as "the risk that a borrower will default on any type of debt by failing to make required payments" (Bis (2000)).

In a business context, default occurs if the value of the issuer's total assets is less than the value of its debt obligations, and the issuer is unable to make the required payments. There are several different approaches to assessing and estimating the probability of default and credit risk. One of these is Structural models, which have the common feature that the company's default depends on its financial and capital structure. The Merton and the Black & Cox models fall within this category.

The Merton model assumes that default can occur only at the maturity of the debt. On the other hand, the Black & Cox model argues that it can occur between the present time and the maturity of the debt. According to the latter, a company defaults if the value of the assets falls below a time-dependent barrier.

In the following subsections, both models are analyzed, highlighting their differences, and in Chapter 4, the empirical analysis using the Black & Cox model is performed.

2.1.1 Merton Distance to Default

The Merton Distance to Default is a market-based measure of corporate default risk, which is inspired by the Merton bond pricing model. In this model's specification is applied the option pricing theory developed by Black and Scholes to the risk of insolvency: the firm's equity is like a call option on the firm's assets with a strike price equal to the face value of a firm's zero-coupon bond debt maturing in T. The restrictive assumptions of the Merton model are as follows: perfect and frictionless market; short-selling of the underlying, as of the derivative instruments is allowed; companies debt structure have only one form of liability which is a zero-coupon bond with maturity in T; the company cannot issue additional debt, enter into a repurchase agreement or pay dividends; there is perfect divisibility of all financial assets; arbitrage opportunities are not permitted; Modigliani-Miller theorem is respected, the firm's value does not depend on its financial structure (Merton (1974)).

On the Probability space (Ω,F,P), the firm's assets value V_t is assumed to follow a geometric Brownian motion hence its dynamics are based on the following stochastic differential equation:

$$\frac{dV_t}{V_t} = \mu dt + \sigma_v dz_t, \quad with \quad V_0 > 0 \tag{2.1.1}$$

Where μ is the firm's value drift rate (the expected annual rate of return on the firm's assets); σ_v is the volatility of firm value; z_t is a standard Wiener process. It follows that the logarithm of the asset value is normally distributed and at time T is:

$$lnV_T \sim N\left(lnV_t + \left(\mu - \frac{\sigma_v^2}{2}\right)T, \sigma_v^2 T\right) \tag{2.1.2}$$

The assumptions of the Merton model state that the firm debt consists of a single bond with face value L and maturity T. The Cash-flow for shareholders at time T is $(V_T$ - $L)^+$ that is the residual value of the firm's asset once the debt is repaid. The probability of default evaluated at time t (P_t) is the probability that the market value of the firm's assets V_T will be less or equal to the book value of the firm's liabilities L at the time of maturity (T):

$$P_t = Pr(V_T \leqslant L) \quad and \quad P_t = Pr(ln(V_T) - ln(L) \leqslant 0) \tag{2.1.3}$$

Under these assumptions, the firm's equity is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt at time to maturity T. According to Black-Scholes-Merton Formula, the value of a firm's equity as a function of the value of the firm can be written as follows:

$$E_t = V_t\phi(d1) - Le^{-rT}\phi(d2) \tag{2.1.4}$$

Where E_t is the market value of the firm's equity at time t; L is the face value of the firm's debt; r is the risk-free rate; ϕ is the cumulative standard normal distribution function; d_1 and d_2 are respectively given by:

$$d_1 = \frac{ln(\frac{V_t}{L}) + (r + \frac{\sigma_v^2}{2})T}{\sigma_v\sqrt{T}} \tag{2.1.5}$$

$$d_2 = d_1 - \sigma_v\sqrt{T} \tag{2.1.6}$$

The Merton model makes use of two critical equations: the first is the Black-Scholes-Merton equation (2.1.4); the second relates the volatility of the firm's value to that of its equity by estimating from Ito's lemma that the value of firm's equity is a function of the value of the firm and time as follows

$$\sigma_E = \frac{V_t}{E_t}\frac{\partial_E}{\partial_V}\sigma_v \tag{2.1.7}$$

In the Black-Scholes-Merton model, it can be shown that $\frac{\partial_E}{\partial_V} = \phi(d1)$, so the equation (2.7) can be written as:

$$\sigma_E = \frac{V_t}{E_t}\phi(d_1)\sigma_v \tag{2.1.8}$$

The Merton model uses these two nonlinear equations, (2.1.4) and (2.1.8), to translate the value and volatility of a firm's equity into an implied probability of default: the value of the firm's equity is easy to observe in the marketplace by multiplying the firm's shares outstanding by its current stock price, while the value of the firm is not directly observable; similarly, the volatility of equity (σ_E) can be estimated, but the volatility of the firm (σ_V)

must be inferred. We proceed as follows: the first step is to estimate σ_E from historical data; the second step is the choice of the forecasting horizon and taking the book value of the firm's total liabilities to be the face value of the firm's debt; the third step is to collect values of the risk-free rate and the market equity of the firm; the last and the most significant step is to solve Equation (2.1.4) for values of V and σ_V. Once this numerical solution is obtained, the distance to default, meaning the number of standard deviations that the firm's asset value is away from the default, is computed as follows

$$DD_M = \frac{ln(\frac{V_t}{F}) + (\mu - \frac{\sigma_v^2}{2})T}{\sigma_v^2 \sqrt{T}} \tag{2.1.9}$$

and the corresponding implied probability of default is

$$P_t = \pi_M = \phi(-DD_M) \tag{2.1.10}$$

Finding V_t and σ_v are used an iterative procedure starting from an approximation of the asset value. Then the Black and Scholes method is applied to obtain successive estimates of V_t and σ_v until they converge. Moreover, if the assumptions of the Merton model hold, it is a very accurate default forecast (Bharath and Shumway (2008)).

2.1.2 Black & Cox Distance to Default

The Merton model is far from realistic: the non-stationary structure of the debt leads to the termination of operations on a fixed date, and default can only happen on that date. However, the so-called first-passage models extend the Merton framework by allowing default to happen at intermediate times. Precursors in the definition of such models are, e.g., Black and Cox (1976) who introduce the possibility of default before the maturity of a ZCB. Over the years, many academics have tried to implement the Black & Cox model by redefining the threshold structure differently or creating closed formulas for calculating the probability of default for first-passage-time models.

The assumptions underlying the Black & Cox model are: investors price takers; short sales permitted; markets perfect and free of taxation and transaction costs; firms with an outstanding debt with face value K at maturity T.

On the Probability space (Ω,F,Q), the firm's assets value A_t of a firm's assets follows a geometric Brownian motion hence its dynamics is based on the following stochastic differential equation:

$$\frac{dA_t}{A_t} = \mu dt + \sigma_v dz_t, \quad with \quad A_0 > 0 \tag{2.1.11}$$

Where μ is the firm's value drift rate; σ_v is the volatility of firm value; z_t is a standard Wiener process.

Black & Cox assume that default occurs the first time the value of the firm's assets falls below a time-dependent barrier K(t). It is explained by the bondholders' right to exercise a safety covenant that allows them to liquidate the firm if its value falls below a specified threshold K(t). Therefore, the default time is given by:

$$\tau = \inf\{t > 0 \ : \ A_t < K(t)\} \tag{2.1.12}$$

For the time-dependent barrier, we observe that if K(t) > K, bondholders are always completely covered, which is certainly unrealistic. On the other hand, one should have $K_T \leq$ K for a consistent definition of default. Our choice is to take an increasing time-dependent barrier as follows:

$$K(t) = K_0 e^{kt} \quad with \quad K_0 \leq K e^{-kT} \tag{2.1.13}$$

By considering default as a random variable, the issuer can be declared insolvent at any time between the placement and the maturity of the debt itself. It constitutes a guarantee for the holders of the securities, as they can implement actions to recover their credit when the company's situation is not yet wholly compromised.

The first passage time with default barrier can now be reduced to the first passage time for Brownian motion with drift as follows (Grasselli and Hurd (2010)):

$$\{A_t < K(t)\} = \left\{ z_t + \sigma^{-1}\left(r - \frac{\sigma^2}{2} - k\right)t \leq \sigma^{-1} log\left(\frac{K_0}{A_0}\right)\right\} \tag{2.1.14}$$

We obtain that the risk-neutral probability of default occurring before time t $\leq$ T is

$$Q[0 \leq \tau < t] = Q\left[\min_{s \leq t}\left(\frac{A_s}{K(s)}\right) \leq 1\right] = Q\left[\min_{s \leq t} X_s \leq \sigma^{-1} log\left(\frac{K_0}{A_0}\right)\right] \tag{2.1.15}$$

Where $X_t = z_t$ + mt, m = σ^{-1}(r - $\sigma^2/2 - k$)

Considering that

$$\underline{M}_t^m = \min_{s \leq t} X_s \tag{2.1.16}$$

denote the minimum process for a Brownian Motion with drift ($X_t = z_t$ + mt), the joint probability distribution for ($\underline{M}_t^m$, X_t) is expressible in terms of the following important function:

$$FP(d; m, t) = \phi\left[\frac{d - mt}{\sqrt{t}}\right] - e^{2md}\phi\left[\frac{-d - mt}{\sqrt{t}}\right] \quad with \quad d \geq 0 \tag{2.1.17}$$

Where d = $\sigma^{-1} log$(K$_0/A_0$) < 0

Thus, we obtain the probability of default computed according to the Black & Cox model as follows

$$Q[\min_{s \leq t}(X_t) \leq d] = Q[0 \leq \tau < t] = 1 - FP(-d; -m, t) = \pi_{BC} \tag{2.1.18}$$

In our econometric framework, we consider as a measure of credit risk the Black & Cox Distance to Default (DD_{BC}) given by the following formula:

$$DD_{BC} = -\phi^{-1}(\pi_{BC}) \tag{2.1.19}$$

2.2 Dataset and Variables

Our sample comprises the Euro Stoxx 50 index constituents, a market capitalization-weighted stock blue-chip index designed to represent the 50 largest companies in the Eurozone. In detail, the index contains constituents from nine Eurozone countries: Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands and Spain. It is managed and authorized by STOXX Limited, owned by Deutsche Börse AG.

We partition the sample by the level of CO2 emissions into non-homogeneous terciles: the first tercile (Tercile 1) contains companies with the lowest level of carbon emissions; the second (Tercile 2) contains companies with a medium level of carbon emissions; the third (Tercile 3) contains the companies with the highest level of carbon emissions.

We had considered the period from 2007 to 2021, including the time before and after the Paris Agreement (ratified in November 2016). It allowed us to analyze potential changes in climate change and market prices. The data are collected from Bloomberg and expressed in US dollars. The frequency of all the variables is semi-annually.

2.2.1 The Measure of firms' climate transition risk

This paper aims to test the relationship between distance to default and exposure to climate change. In the previous section, we deepened the distance to default. Here, we analyze the carbon footprint measure, which can be measured alternatively as the amount of Greenhouse Gas (GHG) emissions expressed in thousands of metric tonnes of carbon dioxide equivalent or the carbon intensity, i.e., the ratio between GHG emissions and the company's revenues. This paper focuses on the first measure as the critical environmental metric.

The International Standard Organization (ISO) has updated the ISO 14064 standard on GHG emissions. According to it, standard GHG inventory accounting is carried out within three different categories of greenhouse emissions: Scope_1, i.e., direct emissions, Scope_2, i.e., indirect emissions from energy consumption, and Scope_3, i.e., all other indirect emissions caused by the entire value chain.

In our empirical analysis, the emissions were considered as follows: the first measure refers to direct emissions ($Scope_1$); the second to the sum of direct and indirect emissions from energy consumption (Scope_{1+2}); and the third to the sum of the previous measure (the second) and the indirect emissions caused by the entire value chain (Scope_{1+2+3}). So, we can both assess the Scope_2 impact on Scope_1 and that of Scope_3 on Scope_{1+2}, highlighting the effect of concurrent emissions instead of a single measurement.

2.2.2 Control Variables

To relate the Black & Cox Distance to Default and carbon footprint, we consider the Control Variables identified in the existing literature about corporate features that influence credit risk. In our analysis, we considered the following control variables.

The Debt Ratio, measured as the amount of leverage used by a company in terms of total debts to total assets. It varies widely across industries and tells us that capital intensive companies tend to have much higher debt ratios than others (Zmijewski (1984)).

Profitability, measured as the Operating Margin given by the ratio between operating income and sales. It is important because it provides relevant information on the probability of a firm going bankrupt (Tudela and Young (2003)).

The Retained Earnings Ratio, i.e., the ratio between retained earnings and total assets, is important because it could be used as an equity buffer to deal with potential unexpected growth opportunities and shocks (Zeitun and Tian (2007)).

The Size, i.e., the natural logarithm of total assets: larger firms are expected to have a lower default probability than smaller firms.

The volatility of asset value: for companies, greater volatility means greater risk and, therefore, greater vulnerability.

The Working Capital Ratio, i.e., the ratio between working capital and total assets, which measures short-term liquidity.

Chapter 3

Empirical Analysis

To underline how Black & Cox Distance to Default and Carbon emissions are related, an initial investigation of the data is obtained by partitioning the sample into terciles by the level of CO2 emissions. Subsequently, we compute the distance to default for each tercile according to the Black & Cox model above mentioned, obtaining the following results: the mean and median of the distance to default are respectively 9.3614 and 9.3257 for companies in the first tercile that is the one with the lowest average level of carbon emissions, 4.2322 and 4.3791 for companies in the second tercile and finally 2.4500 and 2.6124 for companies in the third tercile, the one with the highest average level of carbon emissions.

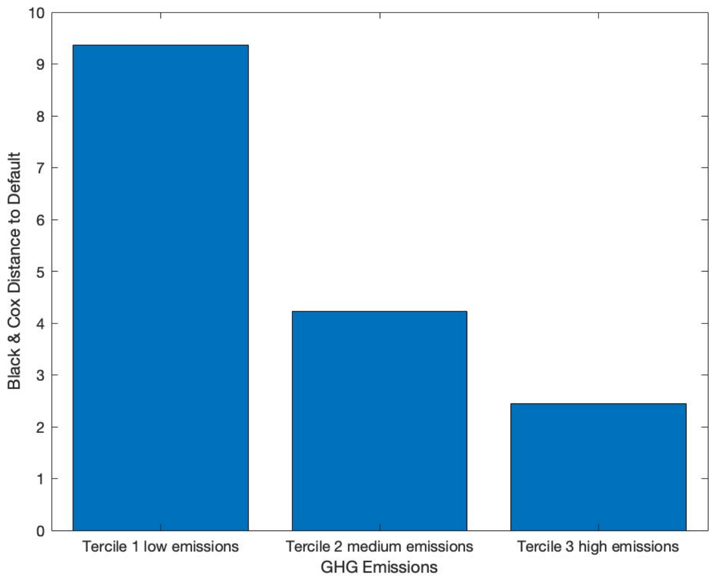
Table 3.1: Results of the Mean and Median of the Black & Cox Default Distance for the index Eurostoxx 50 in the period 2007-2021.

VARIABLE	TERCILE 1	TERCILE 2	TERCILE 3
MEAN	9.3614	4.2322	2.4500
MEDIAN	9.3257	4.3791	2.6124

Table 3.1 shows that the higher the firm's carbon footprint, the smaller its distance to default. In addition, a t-test is run: the values for each tercile state that the null hypothesis of no difference between the averages is rejected with 1% confidence level. Figure 3.1 shows the negative correlation between carbon emissions and Black & Cox Distance to Default,

which is consistent and approximately linear.

Figure 3.1: Distance to default by levels of emissions' terciles for the index Eurostoxx 50 in the period 2007-2021. Y-axis: Black & Cox Distance to Default. X-axis: firm-level transition risk metric proxied by Scope_{1+2+3} emissions.



Before starting with the regression analysis, we perform the Wooldridge test to check the presence of heteroskedasticity and serial correlation. The results confirmed the presence of serial correlation at a confidence level of 1% for each tercile.

We proceed with the regression analysis and implement several robustness checks to rule out the possibility that our results are driven by regulatory changes in high-emitting sectors (energy and extractive) and possible reverse causality, endogeneity and serial correlation issues.

3.1 Results of regression analysis

Our baseline model examines the direct relationship between GHG Emissions and firms' distance to default using the following specification:

$$DD_t = \alpha + \beta X_t + \gamma Y_t + \epsilon_t \tag{3.1.1}$$

Where DD_t is the Black & Cox Distance to Default of firm in year t; X_t is the carbon footprint measured as the amount of CO2 emissions in the following specifications Scope_1, Scope_{1+2}, Scope_{1+2+3}; Y_t is the set of control variables described in the previous chapter. Table 3.2 shows the regression results for each tercile.

Table 3.2: Results of the multivariate analysis with pooled cross-sections OLS of the calculated Black & Cox Distance to Default for the index Eurostoxx 50 in the period 2007-2021. Notation of the significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

VARIABLE	$\beta_{TERCILE1}$	$\beta_{TERCILE2}$	$\beta_{TERCILE3}$
Constant	-1.3178	2.1116	36.8579
Scope_1	-1.6665***	-1.7421***	-0.3512**
Scope_{1+2}	-4.6034***	-3.0467***	-0.3437**
Scope_{1+2+3}	-0.9728**	-0.8749*	-1.4014**
Debt Ratio	-0.6965	-1.4207	-0.0114
Operating Margin	0.7944	1.7437	1.2590
Retained Earnings Ratio	-5.1601	-0.0942	-0.2021
Size	0.1810	0.1706	-0.1614
Volatility	-0.0506	-0.0192	-0.0049
Working Capital Ratio	7.0312	1.0143	1.6290
R^2	0.7768	0.8279	0.9414
Adjusted R^2	0.7025	0.7705	0.9218

From Table 3.2, it can be observed that all regressions have good explanatory power and the natural logarithm of carbon emissions has a very significant negative relationship with the distance to default. The negative coefficients found for Scope_1, Scope_{1+2} and Scope_{1+2+3} emission intensities suggest that market participants consider firms with lower emissions to be less exposed to credit risk because they are associated with a higher distance to default.

In addition, a similarity can be seen in tercile 1 and tercile 2, in which the negative coefficient of Scope_{1+2} almost triples in absolute value in the first tercile and doubles in the second compared to the coefficient of Scope_1; this shows that for low and medium emission firms, Scope_2 has a great impact on the emissions. Furthermore, the coefficient of Scope_{1+2+3} is so weak that it falls below the absolute value of the Scope_1 coefficient, despite the influence of Scope_2. For tercile 3, the negative coefficient relative to Scope_{1+2} is almost equal to that of Scope_1. Moreover, the absolute value of the coefficient of Scope_{1+2+3} more than triples; this shows that for high-emission companies, Scope_3 emissions have a substantial impact.

All the control variables used are indicators of companies' bankruptcy. The relation between the distance to default and the debt ratio is negative and significant; indeed, the higher the debt ratio, the higher the probability that a firm will not survive in the future. The operating margin is positively linked with distance to default because the higher the company's profitability, the higher the distance of default. Reduced volatility of the firm value implies lower risk premiums: lower volatility increases the value of the assets and leads to a rise in the distance to default. Our regression model shows a negative and significant relationship between volatility and distance to default as proof of this. Finally, the working capital ratio, meaning the ability of a company to pay back creditors in the short term, has a positive and significant link with distance to default. Based on the previous observation, companies with positive working capital should not have problems paying their debts; hence, they should have a larger distance to default.

Companies that generate more GHG emissions are more exposed to potential regulatory costs, thus showing less distance to default than companies with lower emissions. This is the reason for which the level of emissions is part of the non-financial data that investors should consider when making economic and financial decisions.

3.2 The impact of the Paris Agreement

A firm's exposure to climate-related transition risk depends on its environmental performance and government policy as an acknowledged risk driver for the climate-related transition. To verify this, we consider the hypothesis stated above, i.e., H2: following the Paris Agreement, firms with a larger carbon footprint increase their credit risk more than firms with a smaller carbon footprint.

Our analysis considers the Paris Agreement an unexpected exogenous event that may have shifted the assessment of credit rating agencies and market participants' perception of climate-related transition risk (Monasterolo and De Angelis (2018)). It may also shed light on the relationship between carbon footprint and distance to default and the importance that financial markets assign to corporate exposure to climate risks. Hence, if carbon footprint influences firms' creditworthiness, we expect firms with a larger carbon footprint at the time of the Paris Agreement show less Distance to Default as financial markets are concerned about exposure to more stringent climate policies. To test this, we construct a Dummy variable (Post Event) that takes value one for 2016 or later and zero otherwise. We thus estimated a second regression using a difference-in-difference model for tercile 3 (higher emissions). Except for the interaction variable between emissions and the Paris Agreement, the others are equal to the previous regression model:

$$DD_t = \alpha + \beta_1 X_t + \beta_2 (X_t * PostEvent) + \gamma Y_t + \epsilon_t \tag{3.2.1}$$

The main coefficient of interest in the regression (3.2.1) is β_2, i.e., the interaction coefficient, which tries to capture the effect of climate agreements on the distance to default of the relative firms with higher GHG emissions. Table 3.3 shows the results of the regression model.

Table 3.3: Results of the multivariate analysis with a difference-in-difference model of the calculated Black & Cox Distance to Default for the index Eurostoxx 50 in the period 2007-2021. Notation of the significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

VARIABLE	$\beta_{TERCILE3}$
Constant	30.8469
Scope_1	-0.4554*
Interaction Variable of Scope_1	-0.0427**
Scope_{1+2}	-0.4838*
Interaction Variable of Scope_{1+2}	-0.0438**
Scope_{1+2+3}	-1.4552***
Interaction Variable of Scope_{1+2+3}	-0.0364**
Debt Ratio	-0.1389
Operating Margin	1.2246
Retained Earnings Ratio	-0.3109
Size	-0.0881
Volatility	-0.0030
Working Capital Ratio	1.0108
R^2	0.9582
Adjusted R^2	0.9415

The relationship between emissions and distance to default is tested for the sample before (2007-2015) and after (2016-2021) the Paris Agreement. The interaction coefficient between GHG emissions and the Paris Agreement has a statistically negative coefficient at a significant level of 5% for each case. This result indicates that there has been a further reduction in the distance to default for firms with higher emission levels since the strengthening of climate policies in the Paris Agreement. Hypothesis 2 is confirmed: companies with a larger carbon footprint, following the Paris Agreement, increase their credit risk more than companies with a lesser carbon footprint. Indeed, the difference between the distance to default calculated before and after the Paris Agreement is higher for companies with a larger carbon footprint, as shown in Table 3.4.

Table 3.4: This table shows that if the Paris Agreement is taken into account, the companies with higher GHG emissions decrease their distance to default more than companies with lesser GHG emissions. $\Delta(DD)$ is the difference between the distance to default calculated before and after the Paris Agreement in the period 2007-2021 for the constituents of the index Eurostoxx 50.

VARIABLE	TERCILE 1	TERCILE 2	TERCILE 3
$\Delta(DD)$	0.0354	0.1749	1.1789

3.3 Robustness checks

Despite the confirmation through the analysis based on the Paris Agreement, we perform further investigations to discard reverse causality issues.

The first check we made is whether our results are driven by regulatory developments aimed at energy and extractive companies; therefore, we perform a regression analysis excluding all energy and extractive companies (only present in tercile 3) using the specification of regression (3.1.1):

$$DD_t = \alpha + \beta X_t + \gamma Y_t + \epsilon_t \tag{3.3.1}$$

We report the regression results in Table 3.5 .

Table 3.5: This table shows the results of the multivariate analysis with pooled cross-sections OLS excluding firms operating in the energy and extractive industries for the index Eurostoxx 50 in the period 2007-2021. Notation of the significance levels: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01.

VARIABLE	$\beta_{TERCILE3}$
Constant	27.5496
Scope_1	-0.2834*
Scope_{1+2}	-0.2444*
Scope_{1+2+3}	-0.5288*
Debt Ratio	-0.0346
Operating Margin	1.1976
Retained Earnings Ratio	0.0645
Size	-0.1622
Volatility	-0.0285
Working Capital Ratio	0.0012
R^2	0.9104
Adjusted R^2	0.8805

A similar trend to that of Table 3.2 can be observed by analyzing the emission coefficients for each tercile. Therefore we discard the possibility that our results are driven by energy and extractive companies. Consistent with Table 3.5, carbon footprint appears to influence distance to default even outside these sectors.

The second check is to avoid the results from endogeneity problems. Therefore, we test variable changes over time in the following regression that should be less vulnerable to the endogeneity bias.

$$\Delta(DD_t) = \alpha + \beta_1 \Delta(X_t) + \gamma \Delta(Y_t) + \epsilon_t \tag{3.3.2}$$

Table 3.6 shows the results of this regression model.

Table 3.6: This table shows a multivariate analysis regression based on changes in the variable for the index Eurostoxx 50 in the period 2007-2021. Notation of the significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

VARIABLE	$\beta_{TERCILE1}$	$\beta_{TERCILE2}$	$\beta_{TERCILE3}$
Constant	0.0146	0.1814	-0.1016
$\Delta(Scope_1)$	-1.3808***	-1.2088***	-0.9690***
$\Delta(Scope_{1+2})$	-3.9265***	-2.0572***	-1.0120***
$\Delta(Scope_{1+2+3})$	-0.6374***	-1.1049***	-1.4489***
$\Delta(DebtRatio)$	-0.4837	-0.0398	-0.8101
$\Delta(OperatingMargin)$	0.7040	1.8443	0.8655
$\Delta(RetainedEarningsRatio)$	-2.9441	-0.0734	-0.2173
$\Delta(Size)$	-0.1189	-0.1531	0.2211
$\Delta(Volatility)$	-0.0321	-0.0328	-0.0042
$\Delta(WorkingCapitalRatio)$	14.2410	1.2324	0.9545
R^2	0.6189	0.8172	0.8638
Adjusted R^2	0.4856	0.7532	0.8162

From the estimated regression, we can infer that changes in the distance to default are negatively related to changes in carbon emissions at a significant level of 1% for each case. Similarly to the previous check, the results of Table 3.6 confirm that changes in the distance to default between 2007 and 2021 are significantly and negatively related to changes in the level of carbon emissions; therefore, we discard the possibility that endogeneity issues drive our results.

Finally, to further address the issue of serial correlation, we add the lags of the dependent variable in our base regression model. We have considered the previous year's Black & Cox

Distance to Default DD_{t-1}, the Black & Cox Distance to Default of 2 years before DD_{t-2} and the Black & Cox Distance to Default of 3 years before DD_{t-3}. The specification of the regression is as follows:

$$DD_t = \alpha + \omega DD_{LAG} + \beta X_t + \gamma Y_t + \epsilon_t \tag{3.3.3}$$

Where DD_{LAG} is a matrix composed by the lags of the dependent variable: DD_{t-1}, DD_{t-2} and DD_{t-3}. We report the regression results in Table 3.7.

Table 3.7: Results of the multivariate analysis including the lags of the dependent variable with pooled cross sections OLS of the calculated Black & Cox Distance to Default for the index Eurostoxx 50 in the period 2007-2021. Notation of the significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

VARIABLE	$\beta_{TERCILE1}$	$\beta_{TERCILE2}$	$\beta_{TERCILE3}$
Constant	24.0504	14.3378	35.1394
DD_{t-1}	0.0992	-0.0655	0.1238
DD_{t-2}	0.1059	-0.1603	0.1270
DD_{t-3}	0.0037	-0.0869	0.0336
Scope_1	-1.3294**	-2.0155***	-1.0058***
Scope_{1+2}	-3.5476***	-3.0570***	-1.0548***
Scope_{1+2+3}	-0.7009**	-0.4857**	-1.6013***
Debt Ratio	-1.1652	-1.1350	-0.2970
Operating Margin	0.6289	1.7861	1.0456
Retained Earnings Ratio	-1.9578	-0.2254	-0.3235
Size	0.0282	0.0297	-0.1045
Volatility	-0.0407	-0.0321	-0.0102
Working Capital Ratio	14.3216	0.6378	1.0212
R^2	0.8759	0.8751	0.9693
Adjusted R^2	0.8069	0.8058	0.9523

Table 3.7 shows that by adding the distance to default from previous years as an explanatory variable, the R^2 of the regressions of tercile 1 and tercile 3 increases significantly, undoubtedly because the distance to default presents a positive serial correlation in each tercile. However, the statistical significance of the emission coefficients remains intact as they remain negatively associated with the dependent variable. These results confirm that distance to default is significantly and negatively related to the level of carbon emissions; therefore, we discard the possibility that serial correlation issues drive our results.

Chapter 4

Comparison with the Benchmark

We have chosen as benchmark the paper Capasso et al. (2020) which investigates the relationship between a firm's exposure to climate risks, expressed as the level of direct GHG emissions (in the specification $Scope_1$), and the Merton Distance to Default, a measure of creditworthiness. One of the limitations of this analysis is the exclusive focus on $Scope_1$ emissions; $Scope_2$ and $Scope_3$ emissions should be considered as well. The other is that Merton model is far from reality because it considers that default can only occur at the maturity of the debt. We contribute to this gap by investigating both a methodological and econometric extension.

4.1 Methodological extension

Assuming default can only occur at debt maturity is an unrealistic scenario; this is the reason for which we decided to estimate the distance to default according to the Black & Cox model. It considers an assumption more relevant to reality in which default can occur when the firm's value falls below a specific time-dependent barrier K(t). Table 4.1 reports the difference between Black & Cox and Merton models in terms of Distance to Default, Probability of Default and Equity Value.

Table 4.1: This table shows the difference between Black & Cox and Merton models in terms of Distance to Default, Probability of Default and Equity value for the index Eurostoxx 50 in the period 2007-2021.

VARIABLE	TERCILE 1	TERCILE 2	TERCILE 3
Merton Distance to Default	13.1291	8.1198	3.1831
Black & Cox Distance to Default	9.3614	4.2322	2.4500
Merton Probability of Default	$1.6728*10^{-7}$	0.0008	0.0106
Black & Cox Probability of Default	$1.1654*10^{-6}$	0.0056	0.0425
Merton Equity	$1.9808*10^{5}$	$0.4795*10^{5}$	$1.0162*10^{5}$
Black & Cox Equity	$1.6745*10^{5}$	$0.4503*10^{5}$	$0.8695*10^{5}$

Table 4.1 shows that the Probability of Default calculated according to the Black & Cox model is higher than that computed with Merton model because penalizing that default there may be before maturity. Consequently, the distance to default calculated according to the first model is smaller than that calculated with the second. In the Black & Cox model, the payoff for shareholders is equivalent to the payoff of a call option and can be priced with the closed-form Black-Scholes expression used for Merton model. According to the results, the equity computed in the Black & Cox model is smaller than that obtained in the Merton model, consistent with the fact that the relative default probability obtained through the former model is greater than that of the latter. It stems because when the default is admitted before maturity, the probability of default increases, and so does shareholders' pressure.

The coefficients relating distance to default and GHG Emissions are negative and significant in both cases. However, using the Black & Cox model, the R^2 of the regressions is slightly higher.

4.2 Econometric extension

In our empirical analysis, we consider three different emission categories: the first measure refers to direct emissions (Scope_1); the second to the sum of direct and indirect emissions from energy consumption (Scope_{1+2}); and the third to the sum of the previous measure (the second) and the indirect emissions caused by the entire value chain (Scope_{1+2+3}). Innovatively concerning studies in the literature, we can assess the impact of Scope_2 on Scope_1 and that of Scope_3 on Scope_{1+2}, highlighting the effect of concurrent emissions instead of single measurements. Table 4.2 reports the results obtained through the base regression model (3.3.1) with Black & Cox Distance to Default as the dependent variable and the natural logarithm of emissions as the independent variable.

Table 4.2: Results of the multivariate analysis with pooled cross-sections OLS to show the intensity of coefficients that relate each category of the emissions and the Black & Cox Distance to Default for the index Eurostoxx 50 in the period 2007-2021.

VARIABLE	TERCILE 1	TERCILE 2	TERCILE 3
Scope_1	-1.6665	-1.7421	-0.3512
Scope_{1+2}	-4.6034	-3.0467	-0.3437
Scope_{1+2+3}	-0.9728	-0.8749	-1.4014

By analyzing the coefficients, one can see a similarity in tercile 1 and tercile 2, in which the negative coefficient of Scope_{1+2} almost triples in absolute value in the first tercile and doubles in the second compared to the coefficient of Scope_1; this shows that for low and medium emission firms, Scope_2 has a great impact on the emissions. Furthermore, the coefficient of Scope_{1+2+3} is so weak that it falls below the value of the Scope_1 coefficient in absolute value, despite the influence of Scope_2. On the other hand, for tercile 3, the negative coefficient relative to Scope_{1+2} is almost equal to that of Scope_1. Moreover, the absolute value of the coefficient of Scope_{1+2+3} more than triples; this shows that for companies of tercile 3, $Scope_3$ has a substantial impact on emissions. It shows how the results have changed considering the three macro-categories of emissions. If we had only looked at the $Scope_1$ emissions, we would have drawn different conclusions in terms of coefficient intensity.

Conclusion

This paper examines how climate-related transition risk and government climate policies influence firms' credit risk. Stricter enforcement of existing environmental laws is expected shortly, which could lead to soaring costs and an impact on issuers' creditworthiness.

The central research question of this paper is whether GHG emissions affect the firm's Black & Cox Distance to Default. The reference sample, the Index Eurostoxx 50, is divided into terciles according to the company's level of emissions. The descriptive statistics reveal the influence of GHG emissions on the distance to default: it is noted that firms in the first tercile (lesser emissions) have a greater distance to default than firms in the third tercile (higher emissions). Initially, strong empirical evidence was found that emissions are negatively associated with distance to default. Subsequently, the distance to default was shown to decrease following regulatory shocks related to stricter climate policies, such as the Paris Agreement. In support of our results, several robustness checks were performed to rule out the possibility that they were driven by regulatory changes in high-emitting sectors (energy and extractive) and endogeneity and serial correlation issues.

Our contribution to the literature is to highlight how a higher level of emissions leads to higher credit risk. We have chosen the Black & Cox Distance to Default to quantify credit risk and three different emission categories ($Scope_1$, $Scope_2$ and $Scope_3$) to measure climate risk, highlighting the effect of concurrent emissions instead of a single measurement. Our results show that corporate creditworthiness is already affected by exposure to climate risks, so rating agencies should further integrate climate risk exposure into their assessment of issuers' creditworthiness. Similarly, banks and credit institutions should consider the carbon footprint of borrowers to assess the risks they are taking effect, and investors in corporate bonds should consider the climate risk exposure of issuers. Overall, robust and standardized approaches should be introduced to address the need to assess global exposure to climate risks.

Future work could consider how credit risk indicators reflect companies' mobilization efforts to move to a low-carbon economy. For instance, metrics related to green investment and innovation efforts, such as R&D investments and green patents, could be considered.

Bibliography

Aldy, J. E. and G. Gianfrate (2019). Future-proof your climate strategy. *Harvard Business Review 4*, 16–24.

Attig, N., S. El Ghoul, O. Guedhami, and J. Suh (2013). Corporate Social Responsibility and credit ratings. *Journal of Business Ethics 117*(4), 679–684.

Barth, F., B. Hübel, and H. Scholz (2022). ESG and corporate credit spreads. *The Journal of Risk Finance*.

Bauer, R. and D. Hann (2010). Corporate environmental management and credit risk. *Available at SSRN 1660470*.

Bento, N. and G. Gianfrate (2020). Determinants of internal carbon pricing. *Energy Policy 143*, 111–115.

Berg, F., J. F. Koelbel, and R. Rigobon (2019). *Aggregate confusion: The divergence of ESG ratings.* MIT Sloan School of Management Cambridge, MA, USA.

Bharath, S. T. and T. Shumway (2008). Forecasting default with the Merton distance to default model. *The Review of Financial Studies 21*(3), 1339–1369.

Billio, M., M. Costola, I. Hristova, C. Latino, and L. Pelizzon (2022). Sustainable finance: A journey toward ESG and climate risk. *Available at SSRN 4093838*.

Bis (2000). *Principles for the management of credit risk final document, basel committee on banking 2 supervision.* BIS Sep.2000. Available at https://www.bis.org/publ/ bcbs75.htm.

Black, F. and J. C. Cox (1976). Valuing corporate securities: Some effects of bond indenture provisions. *The Journal of Finance 31*(2), 351–367.

Bolton, P. and M. Kacperczyk (2020). Signaling through carbon disclosure. *Available at SSRN 3755613*.

Breitenfellner, A., W. Pointner, et al. (2021). The impact of climate change on monetary policy. *Monetary Policy* & *the Economy* (Q3/21), 59–80.

Busch, T., M. Johnson, and T. Pioch (2022). Corporate carbon performance data: Quo vadis? *Journal of Industrial Ecology 26*(1), 350–363.

Capasso, G., G. Gianfrate, and M. Spinelli (2020). Climate change and credit risk. *Journal of Cleaner Production 266*.

Carbone, S., M. Giuzio, S. Kapadia, J. S. Krämer, K. Nyholm, and K. Vozian (2021). The low-carbon transition, climate commitments and firm credit risk. *Available at SSRN 3991358*.

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. *Speech given at Lloyd's of London 29*, 220–230.

Ersoy, H. and C. Musluoglu (2021). Sustainability and banking risks. *PressAcademia Procedia 14*(1), 141–142.

Gianfrate, G. and G. Lorenzato (2018). Stimulating non-bank financial institutions' participation in green investments. Technical report, ADBI Working Paper.

Ginglinger, E. and Q. Moreau (2019). Climate risk and capital structure. *Université Paris-Dauphine Research Paper 3327185*.

Grasselli, M. and T. Hurd (2010). Math 774-Credit Risk Modeling. *Dept. of Mathematics and Statistics, McCaster University*.

Höck, A., C. Klein, A. Landau, and B. Zwergel (2020). The effect of environmental sustainability on credit risk. *Journal of Asset Management 21*(2), 85–93.

Jäger-Waldau, A., I. Kougias, N. Taylor, and C. Thiel (2020). How photovoltaics can contribute to GHG emission reductions of 55% in the eu by 2030. *Renewable and Sustainable Energy Reviews 126*, 109–136.

Kalesnik, V., M. Wilkens, and J. Zink (2021). Green data or greenwashing? do corporate carbon emissions data enable investors to mitigate climate change? *Available at SSRN 3722973*.

Kleimeier, S. and M. Viehs (2016). Carbon disclosure, emission levels, and the cost of debt. *Available at SSRN 2719665*.

Koten, H. (2018). Hydrogen effects on the diesel engine performance and emissions. *International Journal of Hydrogen Energy 43*(22), 10511–10519.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance 29*(2), 449–470.

Monasterolo, I. and L. De Angelis (2018). Blind to Carbon Risk? An Analysis of Stock Market Reaction to the Paris Agreement. *Available at SSRN 3298298*.

Radu, C., M.-A. Caron, and P. Arroyo (2020). Integration of carbon and environmental strategies within corporate disclosures. *Journal of Cleaner Production 244*, 118–131.

Safiullah, M., M. N. Kabir, and M. D. Miah (2021). Carbon emissions and credit ratings. *Energy Economics 105330*.

Schnabel, I. (2020). When markets fail the need for collective action in tackling climate change. *Speech at the European Sustainable Finance Summit*.

Seltzer, L. H., L. Starks, and Q. Zhu (2022). Climate regulatory risk and corporate bonds. Technical report, National Bureau of Economic Research.

Stellner, C., C. Klein, and B. Zwergel (2015). Corporate social responsibility and eurozone corporate bonds: The moderating role of country sustainability. *Journal of Banking and Finance 59*, 538–549.

Tudela, M. and G. Young (2003). A merton-model approach to assessing the default risk of uk public companies. *Available at SSRN 530642*.

Zeitun, R. and G. G. Tian (2007). Does ownership affect a firm's performance and default risk in jordan? *Corporate Governance: The International Journal of Business in Society*.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, 59–82.

Abstract

Climate change is one of the most significant challenges facing humanity this century. The extent of the environmental impact of climate change is still uncertain, but recent scientific evidence is increasingly worrying and many governments are taking decisive action. A transition to a low-carbon economy is therefore unavoidable. A concrete approach to this change requires the activation of a wide range of financial instruments and innovations of various kinds that will have significant implications for all players in the economic scenario: markets, companies, intermediaries and investors. Climate change and global warming are addressed by stricter regulation by governments (e.g., carbon pricing mechanisms), new emerging technologies and changes in consumer behavior. To contain global warming following the Paris Agreement, the most important and decisive climate regulation, European countries and the US have committed to reducing greenhouse gas (GHG) emissions to zero in net terms by 2050 (Jäger-Waldau et al. (2020)). It requires companies to reduce their GHG emissions in the coming years substantially. A company with higher GHG emissions today is more exposed to transition risk and may have a higher probability of bankruptcy and thus a higher credit risk both now and in the future, especially if it does not have a credible plan to transition to a low-carbon economy.

While the relationship between climate risk exposure and stock prices is receiving growing attention in the literature, the impact on corporate bonds appears relatively underexplored (Kleimeier and Viehs (2016); Bolton and Kacperczyk (2020)). Empirical research on the relationship between climate-related transition risk and credit risk has considered environmental scores provided by rating agencies or retrospective environmental metrics such as GHG emissions (Seltzer et al. (2022); Ginglinger and Moreau (2019)). This branch of literature detects that firms with higher GHG emissions or worse environmental scores have a

higher credit risk measured by bond credit ratings, CDS spreads, probability of default or distance to default (Barth et al. (2022); Bauer and Hann (2010); Capasso et al. (2020)).

Our work contributes to the existing literature by investigating the relationship between the Distance to Default and firm credit risk. For this purpose, we consider the constituents of the Eurostoxx 50 index, a market capitalization-weighted stock index designed to represent the 50 largest companies in the Eurozone, over the period 2007-2021. There are several different approaches to estimating credit risk. One of these is the Structural models in which the company's default depends on its financial and capital structure (e.g., Merton and the Black & Cox models). In our paper, as a credit risk measure, we decided to use the Distance to Default computed according to the Black & Cox model, which considers the assumption that default can occur when the firm's value falls below a specific time-dependent barrier (Black and Cox (1976)). On the other hand, Climate risk is measured as the amount of Greenhouse Gas (GHG) emissions with three different categories: Scope1, i.e., direct emissions, Scope2, i.e., indirect emissions from energy consumption, and Scope3, i.e., all other indirect emissions caused by the entire value chain.

In our econometric framework, we partition the sample according to the company's level of emissions into non-homogeneous terciles. The descriptive statistics reveal the influence of GHG emissions on the distance to default: the firms in the first tercile (lesser emissions) have a higher distance to default than firms in the third tercile (higher emissions). Using a panel least squares regression, we show that there is, ceteris paribus, a significant and negative relation between Black & Cox Distance to Default and the level of CO2 emissions. Subsequently, through a difference-in-difference model, we have shown that the distance to default decreases following regulatory shocks related to the implementation of stricter climate policies, such as the Paris Agreement. Finally, after the Paris Agreement, the firms most exposed to climate risk saw their credit risk deteriorate more than firms with lower emissions. In support of our results, several robustness checks were performed to rule out the possibility that they were driven by regulatory changes in high-emission sectors (energy and extractive) and by endogeneity and serial correlation issues. Our results show that corporate creditworthiness is already affected by exposure to climate risks, so rating agencies should further integrate climate risk exposure into their assessment of issuers' creditworthiness.