Integrating Carbon Footprint into Credit Risk Models: A Case Study from the 2022 European Energy Crisis

Simona Ivančová[1]

Petr Teplý[2]

David Tripe[3]

August 2024

Abstract

This paper explores the intersection of climate transition risk and credit risk, leveraging a distinctive dataset from an undisclosed Czech bank containing financial and carbon footprint data of Small and Medium Enterprises during and before the 2022 European energy crisis. Utilizing logistic regression, we first develop a conventional credit scoring model based on client-level financial data, identifying 4 key financial predictors of credit default. We then enrich the model by incorporating 11 carbon footprint variables. Our contribution is four-fold. First, we provide empirical evidence showing that Scope 1 emitters are less prone to credit default, while Scope 2 and Scope 3 emitters are more likely to default. These findings align with the economic context of 2022, where the Czech Republic experienced soaring electricity and gas prices due to post-COVID demand and geopolitical tensions. Scope 1 emitters were less affected by these price hikes, either selling these commodities or having fixed prices. Second, we demonstrate that including Scope 2 carbon footprint improves the credit scoring model's accuracy. Third, we identify four significant financial predictors of credit default, supporting previous research. Our approach offers a more robust framework for assessing credit risk in the context of climate change, highlighting the importance of environmental factors in financial risk management. Finally, we leverage newly available climate risk disclosures to show how they can enhance both climate risk mitigation and banks' credit risk analysis, emphasizing the crucial role of energy use.

Key words: climate risk, ESG, carbon footprint, carbon intensity, logistic regression probability of default, SME

JEL classification: C12, G21, G32

[1] Institute of Sustainable Finance, Faculty of Finance and Accounting, Prague University of Economics and Business, Czech Republic

[2] Institute of Sustainable Finance, Faculty of Finance and Accounting, Prague University of Economics and Business, Czech Republic, corresponding author (petr.teply@vse.cz), corresponding author.

[3] School of Economics and Business, Massey University, Palmerston North, New Zealand; Institute of Sustainable Finance, Faculty of Finance and Accounting, Prague University of Economics and Business, Czech Republic

1. Introduction

Climate risk represents a significant potential loss arising either from extreme natural events or the transition towards a carbon-neutral economy. The transition to a low-carbon economy can involve either gradual interventions (Nordhaus, 2007) or more restrictive policies (Stern, 2009). The European Green Deal is a landmark agreement among European Union member states, setting ambitious targets to reduce carbon emissions by 55% by 2030 and achieve carbon neutrality by 2050 (European Commission, 2019). To meet these goals, high carbon emitters are subject to financial constraints, underscoring the critical role of financial incentives in driving environmental conservation efforts.

Financial institutions, although not direct contributors to carbon emissions, play a crucial role by financing carbon-intensive firms, thereby becoming indirect polluters. In 2018, the European Commission hinted at increasing capital requirements for banks that finance high-carbon industries, highlighting the financial sector's indirect impact on climate change (Dombrovskis, 2018). In the broader business sector, non-financial carbon-intensive firms are already facing regulatory measures such as carbon taxes and emission trading systems, which impose a cost per ton of CO_2 emitted (World Bank, 2020). These climate policies indirectly influence credit default risk, posing a direct impact on financial institutions. Several academic studies have explored the relationship between credit and climate risk, suggesting that carbon pollution levels can be a significant driver of corporate client defaults (Battiston et al., 2017; Capasso et al., 2020). Utilizing a unique dataset from an anonymous Czech bank (the Bank), which includes detailed client-level financial and carbon footprint data (transition risk variables), this study examines how carbon emissions impact the probability of default (PD). The analysis involves a climate-stress test of a standard credit scoring model, integrating transition risk variables to assess their influence on credit risk.

Empirical findings indicate a significant relationship between carbon emissions and credit risk in banking, with various studies highlighting different aspects of this dynamic. Ivanov et al. (2023) show that carbon pricing policies lead to shorter loan maturities, reduced access to permanent bank financing, higher interest rates, and increased participation of shadow banks for high-emission firms, particularly private ones, indicating a swift banking response to transition risks. Mohd & Hishamuddin (2024) suggest that green financing in ASEAN countries can mediate the relationship between climate change and bank stability, implying that sustainable banking practices can help maintain financial stability even as climate risks rise. Bruno & Lombini's (2023) investigation into the global syndicated loan market post-2015 Paris Agreement reveals non-linear relationships between lending variables and CO_2 emissions, with significant policy events like the Paris Agreement amplifying banks' perception of climate transition risk. Thornton et al.'s (2023) analysis of Italian firms further supports these findings, showing that higher default rates on loans are associated with increased GHG emissions, and the Paris Climate Agreement has led to a threshold increase in default rates across almost all sectors, reflecting the adverse impact of transitioning to a lower carbon economy on firm performance. Xinyu et al.'s (2023) results imply that banks may consider a company's carbon footprint as a factor when assessing credit risk. Collectively, these studies underscore that banks are increasingly factoring in carbon emissions and climate policies when assessing credit risk, with significant implications for both financial stability and the broader economy.

We contribute to the literature in four ways. First, this paper provides empirical evidence on the relationship between climate transition risk and credit risk. It uses a stress test of a standard credit scoring model by adding transition risk variables separately, with logistic regression applied for the climate-stress test. The results show that Scope 1 emitters are generally less prone to default, while Scope 2 and Scope 3 emitters tend to default more, consistent with Capasso et al. (2020), Carbone et al. (2021), Thornton et al. (2023) and Xinyu et al. (2023). Second, the study demonstrates that including Scope 2 carbon footprint improves the model's discriminatory power and default prediction accuracy. Integrating Scope 2 and Scope 3 carbon intensity per sales unit also enhances the model's ability to predict non-defaults, aligning with Battiston et al. (2017) and Monasterolo et al. (2017). Third, the paper identifies four significant financial predictors of credit default, supporting the findings of Jakubík & Teplý (2011). It also provides a comprehensive summary of the academic literature on climate transition risk in financial markets, highlighting significant research gaps and suggesting future research directions, as noted by Dunz et al. (2019) and Dafermos & Nikolaidi (2021). Finally, we also contribute by making more extensive use of the disclosures now becoming available on climate risk exposures, and illustrate how these can not only advance objectives relating to climate risk mitigation, but also their usefulness in improving banks' credit risk analysis. We also see how important energy use is in this context.

The remainder of the paper is structured as follows: In Section 2, we discuss key terminology used throughout the paper. Section 3 reviews existing academic literature and identifies gaps that form research hypotheses. Section 4 details the methodology for testing these hypotheses. Section 5 discusses data adjustments and presents descriptive statistics. Against this backdrop, Section 6 introduces our credit risk model and Section 7 discusses its empirical results and compares them with findings from other researchers. Section 8 concludes the paper.

2. Climate and credit risks

This section clarifies the key terminology used in this paper. Section 2.1 introduces the two primary types of climate risk: physical risk and transition risk. Section 2.2 discusses credit risk, which is the main topic of this paper.

2.1 Climate risks

In the context of financial markets, climate risk is driven by two main factors: physical risk and transition risk. This section defines these risks and explains their relevance to the financial system. Although the focus of this research is on transition risk, physical risk is included for completeness. Unless otherwise specified, the definitions of climate risk used in this section are based on those provided by the European Central Bank (ECB, 2020) and the Basel Committee on Banking Supervision (BCBS, 2021).

2.1.1 Physical risk

Physical risk refers to the financial losses resulting from physical damage caused by extreme climate events. The Intergovernmental Panel on Climate Change (IPCC, 2021) identifies two types of events that contribute to physical risk: acute and chronic events. Acute events are sudden extreme weather occurrences such as heatwaves, floods, droughts, storms, and wildfires. Chronic events involve long-term shifts in climate patterns, such as rising sea levels, melting glaciers, and changing temperature patterns. Both acute and chronic events can destabilize the financial system.

The ECB (2020) acknowledges the financial impact of physical risk across four main risk categories: credit risk, market risk, operational risk, and liquidity risk. In terms of credit risk, financial institutions face increased default risk due to higher PD and lower recovery rates. For instance, severe flood events can damage residential properties, leading to mortgage defaults and the destruction of physical collateral. Physical risks are often concentrated in specific geographical areas, meaning that banks operating within these areas may experience significant distress from a single extreme natural event.

2.1.2 Transition risk

Transition risk refers to the financial loss associated with the shift towards a low-carbon economy. This transition can involve policies like carbon pricing or market adjustments. For carbon-intensive industries, transition risk often translates to increased operational or financing costs. Two key concepts define the carbon emissions of a firm. Carbon Footprint is defined as the total amount of carbon emissions directly or indirectly associated with a firm, measured in units of mass of carbon dioxide. Carbon Intensity means the amount of carbon emissions produced per unit of economic output. Countries typically use GDP-based carbon intensity, while firms may use revenue-based or production-based carbon intensity.

According to ECB (2020), carbon emissions are categorized into three scopes: Scope 1 (direct carbon emissions from sources owned or controlled by the firm, such as fuel combustion in company-owned facilities or vehicles), Scope 2 (indirect emissions from the firm’s operations, including purchased electricity, steam, heating, or cooling used in production), and Scope 3 (all other indirect emissions occurring in the firm's value chain). Financial institutions fall under Scope 3 as they finance direct and indirect polluters.

2.2 Credit risk

Credit risk refers to the potential financial loss a lender faces when a counterparty is unwilling or unable to meet their contractual obligations (Jorion et al., 2010). It is the most significant financial risk for the banking sector, as loans constitute the majority of banks' assets. In the context of credit risk, the distribution of returns is typically asymmetrical and left-skewed, meaning the lender's potential upside is capped by the contract, while there is a higher probability of extreme losses than extreme gains (Stepankova & Teply, 2023).

A key measure of credit risk is Expected Loss (EL), which estimates the potential loss to the lender over a specific time horizon. EL is calculated as the product of three components: the probability of default (PD), loss given default (LGD), and exposure at default (EAD). This calculation provides a comprehensive assessment of the credit risk associated with lending activities.

$$EL = PD * LGD * EAD \tag{2.1}$$

PD is a statistical measure that indicates the likelihood of a borrower failing to meet their debt obligations within a specified timeframe. PD is estimated using statistical models that incorporate various quantitative and qualitative factors, such as financial ratios, credit histories, and economic indicators, to assess the creditworthiness of individuals, companies, or entities. Common methodologies for estimating PD include logistic regression and advanced machine learning algorithms (Dumitrescu et al., 2022).

LGD represents the financial loss a lender is likely to incur if a borrower defaults, expressed as (1−recovery rate). The recovery rate is the proportion of the debt that can be recovered. Estimating the recovery rate typically involves analyzing historical data on past defaults to calculate the average or median recovery rate for a specific business segment or type of exposure. For more precise estimations, a discounted cash flow model may be used.

3. Literature Review and Research Hypotheses

This section discusses the literature relevant to the paper. The academic research can be classified into two main strands. First, Section 3.1 explores the impact of climate risk on the resilience of the financial system. Second, Section 3.2 addresses the implications of climate risk for credit risk management. Finally, Section 3.3 formulates the hypotheses after identifying the literature gap. Given the research design of this paper, the focus is placed solely on studies addressing climate transition risk.

3.1 Climate risk impact on financial system

Research on the effect of transition risk on the economy gained prominence mostly after the Paris Agreement in December 2015 (United Nations, 2015), when global economies committed to coordinated efforts to mitigate carbon emissions. The agreement signaled forthcoming climate policies aimed at financially restraining polluting firms and industries. Transition risk is often proxied by the carbon footprint or carbon intensity of the studied subject.

Quantifying transition risk is challenging due to inconsistent reporting of carbon emissions across business sectors (Battiston et al., 2021). Battiston et al. (2017) provided a methodological foundation for conducting climate stress tests on the financial system using data on shareholders of all EU and US publicly listed companies and the loan portfolios of the 50 largest EU banks. Their study revealed that investment and pension funds have the largest holdings of brown assets. Approximately 11.4% of bank assets were exposed to transition risk, suggesting that while the banking sector is currently resilient, this exposure is expected to increase as climate policies intensify (Battiston et al., 2017). Monasterolo et al. (2017) extended this model, examining the weight of each entity's exposure to transition risk on the overall resilience of the financial system. Their findings indicate that government and individual investors are the most vulnerable to transition risk, though their portfolio structures are not systematically significant. In contrast, industry companies and investment funds are the most exposed and crucial. Banks occupy a middle ground in terms of both exposure and importance (Monasterolo et al., 2017).

Studies evaluating individual climate policies assess both their impact on the financial system and their contribution to fostering a green economy transition. Dunz et al. (2019) explored the implications of the Green Supporting Factor (GSF) and carbon tax on the economy. Their study suggests that GSF might have a short-term effect on increasing green lending but may introduce potential trade-offs for financial stability. Furthermore, Dunz et al. (2019) argue that a carbon tax should be complemented with welfare measures to prevent unintended effects on non-performing loans and household budgets. Dafermos and Nikolaidi (2021) also found that GSF and the Brown Penalty (BP) have only a limited effect on increasing green lending. Nevertheless, both studies underline the transition risk stemming from these policies.

3.2 Climate risk implications for credit risk management

Academic studies suggest various approaches for modeling the relationship between credit risk and climate risk, particularly in approximating transition risk. Earlier studies recommended using Environmental, Social, and Governance (ESG) ratings as a proxy for transition risk due to a lack of disclosed data on borrower emissions. However, the direct impact of climate policy on a firm is best determined by its carbon footprint and carbon intensity, making these metrics more accurate determinants of transition risk.

Several studies have utilized ESG ratings to observe climate risk impacts. Oikonomou et al. (2014) examined the effect of ESG ratings on credit spreads and bond ratings, finding that better sustainability ratings can materially reduce the risk premium associated with corporate bonds, thus lowering the cost of corporate debt. These findings are consistent across various sectors. Subsequent studies have found that a higher ESG score correlates with better credit ratings (Devalle, 2017), lower CDS spreads (Blasberg et al., 2021), and lower bond risk premiums (Kotró & Márkus, 2020). Höck et al. (2020) suggested that for firms with high creditworthiness, a higher environmental score is associated with lower leverage and higher market capitalization. Conversely, Chava (2014) argued that firms with multiple environmental concerns tend to incur higher costs on their bank loans.

More recent studies have used direct carbon emissions as an observed variable. Jung et al. (2018), using panel regression analysis, found that the cost of bank debt for Australian firms increases with a higher carbon footprint. Wang et al. (2021), employing the Generalized Method of Moments, discovered that firms with higher carbon footprints face stricter loan covenants and tighter repayment schedules. Zhang et al. (2023), using pooled OLS regression, indicated that higher Scope 1 emissions lead to increased CDS spreads, while Scope 2 and 3 emissions are not yet priced by the credit market.

Several recent academic papers focus on direct drivers of credit risk, such as PD, DD or EDF, and their dependence on the borrower's carbon footprint. Capasso et al. (2020) demonstrated that DD is negatively correlated with a firm's carbon footprint and carbon intensity, implying that firms with higher carbon footprints have a lower distance to default and are more likely to default. They used market data on 458 companies from 2007 to 2017 and identified COP21 as an exogenous policy shock, with significantly lower DD for carbon-intensive firms post-2015.

Carbone et al. (2021) performed a similar analysis using stock data on 558 large US and EU companies from 2010 to 2019, concluding that high emissions are associated with higher credit risk. However, disclosing emissions and setting forward-looking environmental commitments can mitigate this effect. Kabir et al. (2021) extended this research to over 2,700 firms from 42 economies, finding a similar causal relationship between firm DD and emissions, with ROA and cash flow volatility serving as potential channels through which a firm's carbon footprint affects DD. Faralli & Ruggiero (2022) employed EDF as a measure of credit risk along with carbon footprint to investigate their causal relationship. Using data from 1,841 firms from 2008 to 2019 in fixed-effect panel regression, they observed that emission levels are relevant to PD, primarily through the asset volatility channel. They also identified an effect of COP21 on the riskiness of polluter firms. Nguyen et al. (2023) followed up on Capasso et al. (2020), studying S&P 500 firms from 2010 to 2019, and found that the negative effect of transition risk on firms' distance to default is stronger for firms headquartered in states with carbon pricing. Lastly, Bell & van Vuuren (2022) simulated corporate equity price projections using Geometric Brownian Motion to approximate the effects of climate policy shocks. These inputs were used to estimate a climate-stressed PD, revealing negligible increases in PDs for highly rated credit, but a significant impact of policy shocks on lower-quality credit.

3.3 Formulation of the hypotheses

Based on the literature review, there is substantial evidence suggesting a potential relationship between transition risk and credit risk. Leveraging the unique dataset provided by the Bank, which includes data on Small and Medium Enterprise (SME) loans as well as client-level financial and carbon footprint information, this paper will investigate the impact of client carbon emissions on the probability of loan default. This paper builds upon the research conducted by Ivančová (2024), formulating hypotheses and drawing relevant conclusions from them. The hypotheses guiding this examination are as follows:

- Client's carbon footprint increases the odds of defaulting on a SME loan from the Bank.
- Client's financed carbon footprint increases the odds of defaulting on a SME loan from the Bank.

- Client's carbon intensity increases the odds of defaulting on a SME loan from the Bank.
- Client’s carbon intensity per earning asset increases the odds of default on a SME loan from the Bank.

4. Methodology

This section details the method chosen for the empirical analysis. First, Section 4.1 introduces the concept of logistic regression. Second, Section 4.2 focuses on the estimation and evaluation of logistic regression models.

4.1 Logistic regression

Logistic regression is a statistical method used to estimate the probability of a binary outcome. It is widely used in bank credit risk management for several reasons, primarily due to its simplicity, interpretability, and effectiveness in binary classification tasks such as determining creditworthiness (Hand & Henley, 1997; Cramer, 2003; Nithi et al. 2021; Dumitrescu et al., 2022; Kočenda and Iwasaki, 2022). The linear form of logistic regression with n features can be expressed as the natural logarithm of the odds ratio (Mays, 2001):

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \tag{4.1}$$

$$\frac{P}{1-P} = e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i} \tag{4.2}$$

$$P = e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i} - P e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i} \tag{4.3}$$

$$P = \frac{e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i}}{1 + e^{\beta_0 + \sum_{i=1}^{n} \beta_i X_i}} \tag{4.4}$$

$$P = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i X_i)}} \tag{4.5}$$

where:

- represents the probability of default of the firm at the one-year forecast horizon
- $\frac{P}{1-P}$ expresses the odds of an observed event occurring,
- β_i denotes a vector of coefficients of the model,
- X_i represents a vector of independent variables.

If the coefficient estimate for a predictor is negative, an increase in that predictor decreases the odds of the event occurring, and vice versa. Logistic regression requires several assumptions to be met. The dependent variable must have a binary outcome, either 1 or 0, with mutually exclusive classes—no observation can belong to both. The classes should be balanced to avoid bias towards the majority class. The relationship between the dependent and independent variables must be linear. There should be no perfect separation of the classes, meaning the odds estimates should not be exactly 1 or 0. Additionally, logistic regression assumes no multicollinearity, which means predictors should not be highly correlated. Multicollinearity can be identified using a correlation matrix or by calculating the Variance Inflation Factor (VIF) for each predictor. VIF is the ratio of the variance of a coefficient when fitting the full model to the variance of a coefficient when fitting a single-variable model. A VIF value between 5 and 10 indicates moderate correlation, while a value above 10 suggests severe correlation with another predictor (Greene, 2003).

Logistic regression is a standard method for assessing the credit risk of potential clients (Jakubík & Teplý, 2011). Compared to more sophisticated machine learning models like neural networks or decision trees, logistic regression is preferred for its simplicity and interpretability (Rosenberg & Gleit, 1994; Dumitrescu et al., 2022). A trained logistic model represents a set of parameters on selected financial inputs, estimated using historical data. Financial information on a new potential client is input into the model, which then returns a PD, i.e., a credit score, which is used to decide whether to grant a loan.

4.2 Evaluation of the logistic regression

When the model is specified, its predictive power is tested on an unobserved testing set. The odds returned by the model are translated into binary predictions based on a threshold probability value. If this threshold is set to 0.5, estimates of 0.5 or higher are considered positive, predicting the event will occur, while estimates below 0.5 are considered negative, predicting the event will not occur. These binary predictions are then compared to the actual outcomes in the testing data, and the model's performance is evaluated based on the number of correct matches.

A true positive (TP) prediction means the model correctly predicted the occurrence of an event. A true negative (TN) prediction means the model correctly identified an event not happening. A false positive (FP) prediction, or Type 1 error, occurs when the model predicts an event to happen when it does not. A false negative (FN) prediction, or Type 2 error, occurs when the model fails to predict an event that does occur. A more sensitive model tends to have fewer Type 2 errors, while a more specific model aims to minimize Type 1 errors. In the context of credit risk, a Type 1 error results in the denial of credit to creditworthy clients, whereas a Type 2 error leads to classifying high-risk clients as creditworthy. Therefore, a credit scoring model aims to achieve high sensitivity while maintaining sufficient specificity.

To balance specificity and sensitivity, the Receiver Operating Characteristic (ROC) curve is used in this paper for model assessment. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) for all possible thresholds of the model's predicted probabilities. The area under the ROC curve (AUC-ROC), or AUC score, indicates the model's discriminatory power. An AUC score of 0.5 suggests the model is no better than random guessing, while a score closer to 1 indicates better predictive performance. An AUC score above 0.7 suggests reasonably good discriminatory power. However, the AUC has a drawback in that it ignores class imbalance. Consequently, even a model that fails to detect any defaults can achieve a high AUC score due to the prevalence of correctly identified negative events. Therefore, it is essential to consider both true positive and false positive rates separately, in addition to achieving a high AUC.

Given that this paper employs logistic regression, four new hypotheses are formulated, as new potential academic contributions are identified from the analysis:

- Inclusion of the client's carbon footprint improves the performance of the model for default prediction.
- Inclusion of the client's financed carbon footprint improves the performance of the model for default prediction.
- Inclusion of the client's carbon intensity improves the performance of the model for default prediction.
- Inclusion of the client's carbon intensity per earning asset increases the performance of the model for default prediction.

5. Data Analysis

This section discusses the data used in the empirical analysis. First, the original dataset from the Bank and the adjustments made are introduced in Section 5.1. Second, descriptive statistics of the adjusted data are presented in Section 5.2. Finally, the correlation matrix of all variables is interpreted in Section 5.3.

5.1 Dataset

5.1.1 Data description

We were provided with unique data from the Bank, which is part of a banking group supervised by the ECB. The dataset consists of three parts. First, the dataset includes all active SME loan accounts for the years 2022 and 2023, along with information on defaults in 2023. Second, it includes a list of all active SME clients and their financial information from 2017 to 2022. Finally, a dataset contains total and loan-financed carbon footprint information for all SME clients. One SME client could have several open accounts for different loan products. The Bank noted that if a client defaults on one account, all other accounts are flagged as defaulting as well. Therefore, specific loan type information does not contribute further to the analysis, as it is impossible to confidently determine which account initiated the default. SME clients adhere to the EU's definition of an SME, which includes having fewer than 250 employees, an annual turnover not exceeding €50 million, and a balance sheet total not exceeding €43 million. In the European Union, ESG reporting is governed by the Corporate Sustainability Reporting Directive (CSRD), which mandates that large companies and listed SMEs disclose detailed information on sustainability risks, opportunities, and impacts. This regulation, which builds on the previous Non-Financial Reporting Directive (NFRD), aims to enhance transparency and ensure that investors and stakeholders can make informed decisions based on consistent and comparable ESG data (European Commission, 2022). The Czech Republic is a member of the European Union, which means that Czech companies are subject to EU regulations and directives.

The initial dataset, consisting of 2,329 observations across 69 variables, was created by merging data from the three datasets based on the client ID. We retained only the financial data for 2022 due to a large number of missing values in earlier years. New predictor variables derived from the provided data were added, resulting in an initial dataset of 2,329 observations on 39 variables. The dataset includes 31 default observations and 2,298 non-default observations.

Our study is among the first to utilize firm-level carbon emissions data, which were calculated by the Bank based on detailed questionnaires completed by its clients. Since not all SMEs in the Czech Republic report their carbon footprint, the data include approximations derived from sales for firms in specific industries, classified according to NACE codes applied in the EU. This unique dataset allows us to empirically analyze the impact of carbon emissions on credit risk. The carbon footprint data provided by the Bank includes detailed information on Scope 1, Scope 2, and Scope 3 emissions. Highlighting this data source in our discussion underscores the novelty and significance of our research. Such disclosures are crucial for understanding how environmental factors influence financial stability, as they provide comprehensive insights into firms' carbon emissions and their associated risks.

5.1.2 Adjustments to the dataset

Three major issues with the initial dataset required adjustments to proceed with the analysis: the amount of missing values in the subset of defaulting clients, a large number of extreme values, and class imbalance, i.e., the small number of default observations (Jorion et al., 2010). These issues were handled using standard empirical research approaches: data imputation, data partition, winsorization and oversampling.

To address missing values, we used data imputation, replacing missing observations with selected sample statistics. This technique helps prevent further loss of default observations. We impute only default observations, while missing values of non-default observations are omitted. The sample median was chosen as the statistic for imputation due to its robustness against outliers (Jorion et al., 2010). For 17 out of 31 default observations missing financial data from 2022, we used data from 2021. For the remaining six observations, we imputed the medians for every missing value.

The data were split into a training set for model preparation and a testing set for model validation, with a 55:45 ratio favoring the training set. The distributions of the sample and the defaulting subgroup were checked to ensure they corresponded between the training and testing sets. Random partitioning was repeated until the most corresponding distributions were achieved, recognizing the challenge of achieving identical distributions with a small default sample.

Winsorization was applied to handle extreme values by computing the upper and lower percentiles of the data distribution and replacing values exceeding these thresholds with the respective percentile values. This preserves data while maintaining the original distribution. Winsorization was applied separately to the training and testing sets to prevent data leakage. The thresholds were derived from the training set and applied to both sets. The lower percentile was set at 1% and the upper percentile at 99% (Leone et al., 2019).

To address class imbalance, we used the Synthetic Minority Over-sampling Technique (SMOTE), which generates synthetic samples for the minority class in the training data. This prevents bias towards the majority class. Before adjustment, defaults represented 2.25% of the training set. We aimed for a default proportion of 10%, reflecting the reality of non-performing loan ratios in Europe, which ranged from around 2% to over 10% in 2022 (Huljak et al., 2022). The SMOTE algorithm creates synthetic examples by selecting k-nearest neighbors for each minority class observation and generating samples at randomly selected points between the observation and its neighbors (Douzas et al., 2018). Given the small number of original observations, the original and oversampled distributions are not perfectly identical, but the oversampled distribution of defaults closely mirrors the original data. Table 1 shows the number of observations after the adjustments were made.

Table 1: Observation Count After Adjustments

Adjustment	**Non-defaults (0)**	**Defaults (1)**
Original Data	2,298	31
Imputation	1,375	31
Partition		
- Train Data	757	17
- Test Data	618	14
Winsorization		
- Train Data	757	17
- Test Data	618	14
Oversampling		
- Train Data	757	85
- Test Data	618	14

Source: Authors

5.2 Descriptive statistics

This subsection provides a descriptive analysis of the adjusted data as outlined previously. Given that the data was divided into training and testing sets to ensure corresponding distributions of all predictors, we present the descriptive statistics of the combined training and testing sets prior to oversampling, assuming both subsets exhibit similar patterns.

5.2.1 Dataset

The default flag for the year 2023 is used as the dependent variable in the analysis. The dataset includes two qualitative variables: the NACE (Nomenclature of Economic Activities) code of the industry sector and the postal code of the client's headquarters. The potential predictors in the dataset are categorized into two main groups: transition risk variables and financial predictors. The NACE code is a four-digit code used within the EU to classify business activities. The first digit indicates a high-level industry sector of a firm. Table 2 shows the number of clients in the dataset per industry sector and the proportion of defaults in each sector. Table 3 presents the average emissions per industry sector observed in the dataset.

Most of the sample belongs to category (4), which is characterized by Scope 3 emissions and represents roughly 75% of the total average emissions. Category (2), which has the second highest default proportion, reports around 80% of its total average emissions as Scope 3. The most polluting categories in terms of total average emissions are categories (3) and (2). The least polluting industry sector is category (6), the financial sector. The largest Scope 1 emitters (direct emissions from production) belong to categories (3) and (1). The largest Scope 2 emitters (indirect emissions from purchased energy) are in categories (2) and (8). The largest Scope 3 emitters (indirect emissions from the supply chain) are found in categories (2) and (3). Across all categories, Scope 3 emissions constitute the majority of the average emissions, with Scope 1 emissions usually being the second largest.

To align with the European Union's regulatory landscape, it's important to note that the EU has implemented stringent mandates on corporate ESG reporting, particularly through the above-mentioned CSRD. Under this directive, firms are required to disclose detailed information on their environmental impact, including Scope 1, Scope 2, and Scope 3 emissions. This mandate enhances transparency and holds companies accountable for their entire value chain's carbon footprint. Consequently, firms in categories with high Scope 3 emissions, like categories (2) and (3), face increased scrutiny, as they must comprehensively report their indirect emissions and outline strategies for mitigation.

Table 2: Industry sector of clients

Industry sector	N. of observations	Proportion of defaults
(1) Agriculture, forestry and fishing	241	2.90 %
(2) Manufacturing, mining and quarrying	250	3.60 %
(3) Construction	90	1.11 %
(4) Wholesale, retail, transportation, accommodation and food services	650	1.69 %
(5) Information and communication	29	0.00 %
(6) Finance and insurance	73	2.74 %
(7) Real estate	55	0.00 %
(8) Professional, scientific, technical and administration services	24	4.17 %
(9) Public administration, defense, education, human health and social work	24	0.00 %

Source: Authors based on the Bank´s database

Table 3: Average carbon footprint per industry sector (mil.m³ CO_2)

Industry sector	Scope 1	Scope 2	Scope 3
(1) Agriculture, forestry and fishing	2,265	190	3,148
(2) Manufacturing, mining and quarrying	907	395	5,269
(3) Construction	3,271	209	3,684
(4) Wholesale, retail, transportation, accommodation and food services	573	43	1,836
(5) Information and communication	1,094	162	3,338
(6) Finance and insurance	383	77	785
(7) Real estate	523	61	1,622
(8) Professional, scientific, technical and administration services	606	265	2,893
(9) Public administration, defense, education, human health and social work	119	119	940

Source: Authors based on the Bank´s database

Table 4 presents the descriptive statistics for both total and financed carbon footprints. The Bank was unable to provide separate financed carbon footprint data for Scope 1 and Scope 2 emissions. The largest proportion of emissions is attributed to Scope 3 for both total and financed carbon footprints, while Scope 2 carbon emissions represent the smallest portion of the emissions in the sample. The distributions of all variables are right-skewed, indicated by medians that are significantly lower than the means.

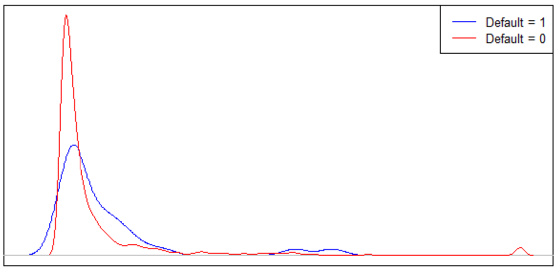
Table 4: Descriptive statistics of carbon footprint (ths. m^3 CO_2)

Statistic	Mean	St. Dev.	Min	Median	Max
Carbon Footprint					
Scope 1	1,087,094	2,277,454	6,731	330,17	16,342,336
Scope 2	151,978	306,767	19,881	41,067	1,851,534
Scope 3	2,760,649	3,870,008	13,2	1,309,172	22,101,437
Financed Carbon Footprint					
Scope 1 and 2	180,095	377,352	0	52,03	2,285,294
Scope 3	389,81	652,077	0	157,402	3,935,159

Source: Authors based on the Bank´s database

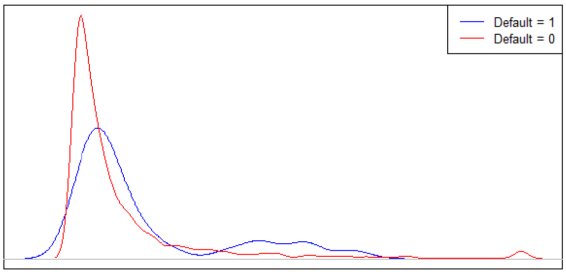
Examining the distributions of financed carbon footprints for defaulting and non-defaulting subsets reveals that the median financed carbon footprint for defaulters is significantly higher than that for non-defaulters. This pattern is evident both in the case of Scope 1 and 2 financed footprints, as shown in Figure 1, and in the Scope 3 financed footprint, as shown in Figure 2. No other carbon footprint variable exhibited a distinctively higher median in the distribution of defaulters.

Figure 1: Distribution of Scope 1 and 2 financed carbon footprint



Source: Authors based on the Bank´s database

Figure 2: Distribution of Scope 3 financed carbon footprint



Source: Authors based on the Bank´s database

5.2.2 Financial predictors

The Bank provided a set of 13 financial variables: Gross Sales, Total Turnover, Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA), Pre-tax Earnings, Non-current Assets, Current Assets, Total Assets, Net Profit, Total Debt, Equity, Total Liabilities, Cash, and Operating Cash Flow. Current Liabilities were derived as the difference between Total Liabilities and Non-current Liabilities. From the original financial data, 10 financial predictors commonly used in credit scoring models were derived, as demonstrated by Jakubík and Teplý (2011), who also utilized data reported according to Czech Accounting Standards. Table 5 lists these derived financial predictors, their definitions, and optimal values. The ratios are categorized based on the aspects of the firm's financial health they represent. Table 6 provides descriptive statistics for these financial predictors.

Table 5: List of derived financial predictors

Predictor	Description	Healthy Value
Liquidity Ratios		
Current Ratio	Current Assets / Current Liabilities	> 1.5
Operating Cash Flow Ratio	Operating Cash Flow / Current Liabilities	> 0.5
Profitability Ratios		
Return on Equity (ROE)	Net Profit / Equity	> 0.1
Return on Assets (ROA)	Net Profit / Total Assets	> 0.05
Profit Margin	Net Profit / Gross Sales	> 0.03
Operating Cash Flow Margin	Operating Cash Flow / Gross Sales	> 0.1
Solvency Ratios		
Debt to Equity Ratio	Total Debt / Equity	< 2.0
Debt to Assets Ratio	Total Debt / Total Assets	< 0.4
Equity Ratio	Equity / Total Assets	> 0.4
Economic structure indicators		
Debt to Capital Ratio	Total Debt / (Equity + Total Debt)	< 0.5

Source: Authors

When comparing the median or mean values to the optimal values, most of the ratios appear to be roughly aligned with the expectations. For liquidity measures, the median Current Ratio suggests that the sample firms are generally liquid, while the median Operating Cash Flow Ratio falls below the liquidity threshold. In terms of profitability, the sample firms are slightly underperforming. Solvency and economic structure indicators are consistent with expectations.

Table 6: Descriptive statistics of financial predictors

Statistic	Mean	St. Dev.	Min	Median	Max
Current ratio	3.004	2.455	0.185	2.275	12.955
Cash Flow ratio	0.760	0.950	-0.508	0.458	5.181
ROE	0.159	0.336	-1.147	0.122	1.727
ROA	0.057	0.084	-0.182	0.043	0.374
Profit margin	0.049	0.106	-0.400	0.031	0.564
Cash Flow margin	0.127	0.173	-0.164	0.076	0.886
Debt to Equity	1.456	3.375	-11.041	0.644	21.547
Debt to Assets	0.309	0.197	0.002	0.280	0.835
Equity ratio	0.403	0.226	-0.087	0.403	0.873
Debt to Capital	0.442	0.268	0.001	0.41	1.205

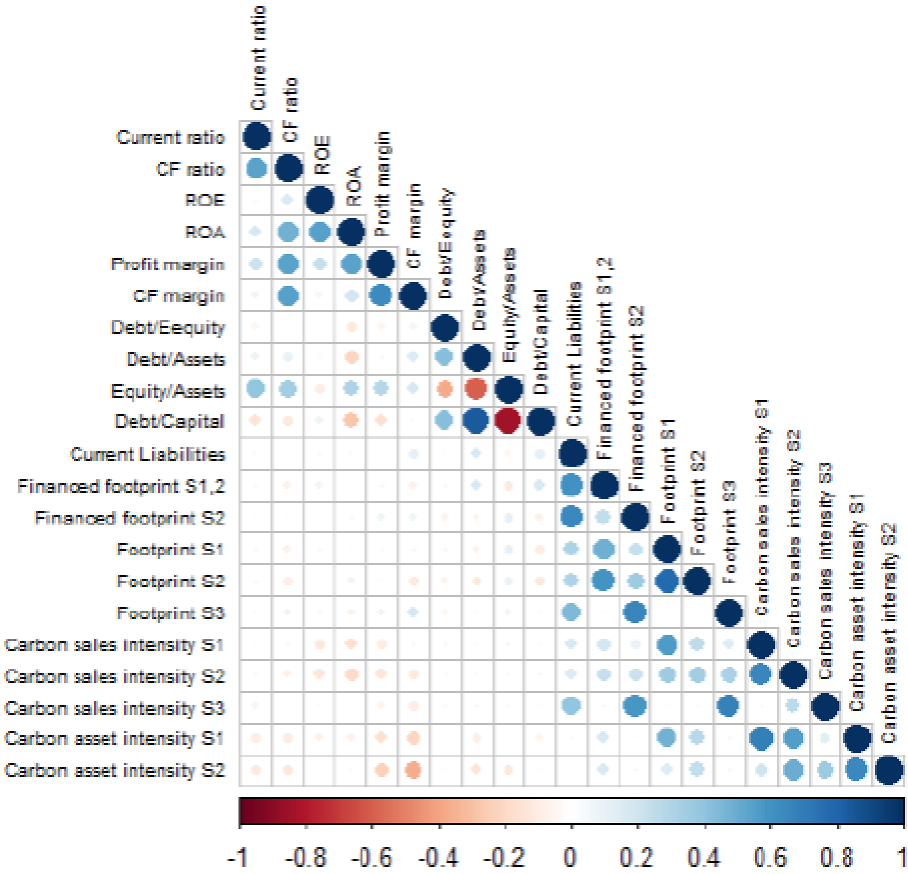
Source: Authors

Comparing the median and mean values to the optimal values, we observe that these values generally align with expectations for most ratios. The median Current Ratio indicates that the sample firms are liquid, while the median Operating Cash Flow Ratio is below the optimal liquidity threshold. Profitability measures show that the sample firms are slightly underperforming, but solvency and economic structure indicators are consistent with expectations.

5.3 Correlation matrix

Figure 3 presents the correlation matrix of all variables included in the dataset. Transition risk variables exhibit light to moderate positive correlations with each other, but they are not included in the same model simultaneously. There is a moderate to strong correlation between the Equity ratio, Debt-to-Capital, Debt-to-Assets, and Debt-to-Capital, indicating potential multicollinearity if these variables are included together. Specifically, the correlation coefficient between the Equity ratio and Debt-to-Capital is -0.836, between the Equity ratio and Debt-to-Assets is -0.599, and between Debt-to-Capital and Debt-to-Assets is 0.838. The Debt-to-Equity ratio is not strongly correlated with any of these predictors. Additionally, there is a moderate correlation between the Profit margin, Operating Cash Flow margin, and Operating Cash Flow ratio. Furthermore, a moderate correlation exists between Current Liabilities and the Scope 3 financed carbon footprint, with a correlation coefficient of 0.642.

Figure 3: Correlation matrix



Source: Authors

6. The Model

The final step in preparing for the empirical analysis is constructing a standard model for estimating PD. This standard model will be climate-stressed in Section 7 using transition risk variables to observe their effects. Thus, the model should capture as much endogeneity in the data as possible and be able to correctly identify defaults.

6.1 Model specification

A credit scoring model for SME loans should be built on four key financial dimensions of a firm. These dimensions include liquidity, which captures the short-term financial viability of a firm; solvency, reflecting the long-term financial health of a firm; profitability, which assesses the ability of a firm to generate earnings relative to underlying factors; and economic structure, providing insight into the capital structure of a company (Bartual Sanfeliu et al, 2012).

Based on the literature on credit scoring models (Ohlson, 1980; Sironi & Resti, 2007; Jakubík & Teplý, 2011), a set of 10 financial ratios and 4 financial inputs were selected as potential predictors in the model. The values of the 4 financial inputs were standardized to avoid bias caused by different scales of variables. All potential predictors were estimated in a simple model to examine their significance and the sign of the estimator. Table 7 features the estimators of these simple models. The effects of the predictors, i.e., the signs of the estimators, align with expectations regarding their impact on the odds of default. Surprisingly, the debt estimator has a negative sign, suggesting that more debt lowers the chances of default. However, this estimate carries low weight and lacks statistical significance.

The estimate for Current Liabilities is negative and significant, as an increased value implies fewer long-term debts and, consequently, lower interest expenses. Both the Operating Cash Flow margin and Operating Cash Flow ratio are strongly significant and have the lowest values of the Akaike Information Criterion (AIC), indicating that these variables might represent the best fit for the data.

Table 7: Simple models

Predictor	Coefficient	AIC	Significance
Operaing CF ratio	-2.575	477	***
Operating CF margin	-11.753	484	***
Equity ratio	-3.358	518	***
ROA	-9.177	522	***
ROE	-1.607	535	***
Profit margin	-4.494	539	***
Equity	-0.596	544	**
Current ratio	-0.199	545	**
Debt-to-Assets	1.638	547	**
Current Liabilities	-0.404	550	*
Assets	-0.385	550	*
Debt-to-Capital	0.769	552	
Debt-to-Equity	0.018	555	
Debt	-0.043	555	

Source: Authors

The model was trained using incremental feature selection, i.e., by progressively adding features one by one and observing their effect on the goodness of fit and model performance. Two models were selected as potential standard models for climate-stressing. Table 8 summarizes the two models. The simpler model (Model 1) includes all pillars except for the solvency ratios, which were not significant in any model. Model 2 is a more complex version of the first model and includes a solvency indicator.

Table 8: Summary of the logistic regression

	Dependent variable:	
	flag_default	
	(1)	(2)
Operating_CF_margin	−4.551*	−4.082*
	(2.504)	(2.428)
Operating_CF_ratio	−1.561***	−1.686***
	(0.561)	(0.561)
Current_liabilities	−0.630**	−0.590**
	(0.271)	(0.269)
Equity_ratio	−2.225***	−1.893***
	(0.621)	(0.696)
Debt_to_Assets		0.809
		(0.713)
Constant	−0.796***	−1.150***
	(0.215)	(0.385)
Observations	842	842
Log Likelihood	−221.914	−221.266
Akaike Inf. Crit.	453.828	454.532
Note:	*p<0.1; **p<0.05; ***p<0.01	

Source: Authors

The simpler model (Model 1) includes all financial dimensions except for the solvency ratios, which were not significant in any model. Model 2 is a more advanced version of Model 1, adding a solvency indicator (debt-to-asset ratio). As shown in Table 9, there is no significant multicollinearity in the selected models, as the VIF values are well below 5. The estimates of the two models are quite similar, with minor differences, and the levels of significance remain comparable. The Operating Cash Flow margin has the most significant impact on PD, although its statistical significance is the weakest.

Table 9: Variance inflation factors

Model	CF margin	CF ratio	Equity ratio	Current liab	D/A
(1)	2.429	2.478	1.046	1.022	
(2)	2.411	2.480	1.272	1.039	1.260

Source: Authors

Table 10 presents the number of correct and false predictions of the models on the testing set, along with the specificity and sensitivity rates. As expected, the severe class imbalance caused the model estimates to be biased toward the majority class, resulting in no defaults being correctly indicated using a threshold of 0.5. Initially, defaults represented only 2.2% of the training sample, and this proportion was synthetically balanced to 10% as discussed in Section 5.1.2.

Table 10: Evaluation of model performance

Model	TN	FN	TP	FP	Specificity	Sensitivity
Model (1)	614	14	0	4	0.9935	0
Model (2)	615	14	0	3	0.9951	0

Source: Authors

To demonstrate the predictive power of the model without the influence of class imbalance bias, we replicated all the default observations in the training set eight times to create a more balanced panel. This resulted in 680 default observations and 757 non-default observations. The models were then estimated using this balanced training data, as shown in Table 11. There were no major changes in the values of the estimators, and all estimators now exhibit strong statistical significance. The value of the constant increased significantly due to the higher frequency of default occurrences in the balanced dataset, which also increased the odds of a default happening.

Table 11: Summary of the logistic regression (balanced data)

	Dependent variable:	
	flag_default	
	(1)	(2)
Operating_CF_margin	-4.485^{***}	-4.201^{***}
	(1.177)	(1.142)
Operating_CF_ratio	-1.403^{***}	-1.621^{***}
	(0.251)	(0.256)
Current_liabilities	-0.811^{***}	-0.780^{***}
	(0.149)	(0.153)
Equity_ratio	-2.774^{***}	-2.108^{***}
	(0.365)	(0.381)
Debt_to_Assets		1.912^{***}
		(0.421)
Constant	1.379^{***}	0.566^{***}
	(0.132)	(0.213)
Observations	1,437	1,437
Log Likelihood	−740.828	−730.510
Akaike Inf. Crit.	1,491.656	1,473.019
Note:	*p<0.1; **p<0.05; ***p<0.01	

Source: Authors

Examining the performance of the models estimated on balanced data, Table 12 shows that Model 1 is more effective at identifying defaults than Model 2, as it has a higher number of TP predictions.

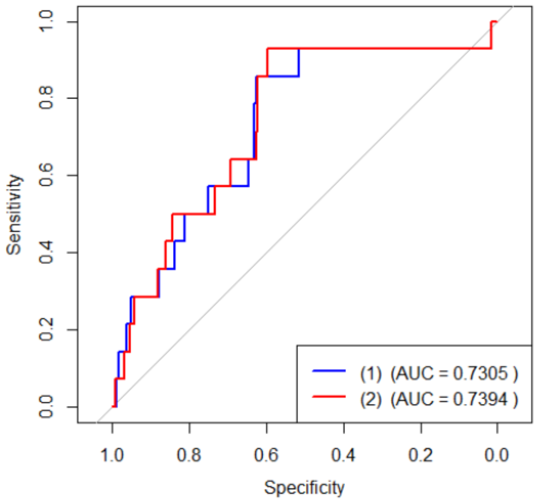
Table 12: Evaluation of model performance (balanced data)

Model	TN	FN	TP	FP	Specificity	Sensitivity
Model (1)	456	6	8	162	0.738	0.571
Model (2)	455	7	7	163	0.736	0.500

Source: Authors

The AUC values, presented in Figure 4, are almost equal for both models, indicating that both have moderately good discriminatory power. However, Model 1 is slightly more sensitive, suggesting it may be better at avoiding Type 2 errors, which involve failing to predict a default.

Figure 4: ROC curve (balanced data)



Source: Authors

6.2 Robustness check

The robustness of the models was assessed by applying the models to data adjusted using alternative parameters from those described in Subsection 5.1.1. The data was randomly partitioned with a 60:40 ratio, and winsorization percentiles were set to 99.5% for the upper threshold and 0.5% for the lower threshold. Defaults in the training set were oversampled to represent 8% of the training sample. The distributions of key predictors were consistent across the training and testing samples. The training data were balanced in a similar manner as described in the previous section.

To conclude, the models were estimated on two different random partitions of the data, yielding similar estimators and achieving comparable effectiveness in default detection (detail results are not presented in the paper but available on request). Model 1 is chosen to be climate-stressed in Section 7, as it correctly predicted more defaults and all its variables are statistically significant.

7. Results

This section is organized based on the hypotheses set forth in Sections 3.3 (Hypotheses 1, 3, 5, 7) and Section 4.2 (Hypotheses 2, 4, 6 and 8). The results are summarized in Section 7.9, and further research opportunities are presented in Section 7.10. The final list of hypotheses is as follows:

- Hypothesis 1: Client's carbon footprint increases the odds of default on a SME loan from the Bank
- Hypothesis 2: Inclusion of the client's carbon footprint increases the performance of the model for default prediction.
- Hypothesis 3: Client's financed carbon footprint increases the odds of default on a SME loan from the Bank.
- Hypothesis 4: Inclusion of the client's financed carbon footprint increases the performance of the model for default prediction.
- Hypothesis 5: Client's carbon intensity per unit of sales increases the odds of default on a SME loan from the Bank.
- Hypothesis 6: Inclusion of the client's carbon intensity per unit of sales increases the performance of the model for default prediction.

- Hypothesis 7: Client's carbon intensity per earning asset increases the odds of default on a SME loan from the Bank.
- Hypothesis 8: Inclusion of the client's carbon intensity per earning asset increases the performance of the model for default prediction.

To test the hypotheses, the standard model featured in Section 6 was climate-stressed separately using all types of transition risk variables. The values of carbon footprint and financed carbon footprint were standardized to avoid bias due to different variable scales. For robustness, the analysis was repeated using the alternative data also employed in the standard model robustness check in Section 6. This subsection presents the models estimated on balanced data to compare their ability to correctly estimate defaults. Models estimated on imbalanced data generated similar values and significance of parameters (detail results are not reported in the paper but are available on request).

7.1 Hypothesis 1 testing

7.1.1 Baseline results

Table 13 summarizes the standard and climate-stressed models. It reveals that several financial and environmental factors significantly impact the probability of default for SME clients. Key financial predictors such as the Operating Cash Flow margin, Operating Cash Flow ratio, and Equity ratio all have highly significant negative coefficients, indicating that better financial health reduces default risk. The Current liabilities variable also shows a significant negative relationship with default probability. Conversely, environmental factors like Scope 2 and Scope 3 total emissions are highly significant with positive coefficients, suggesting that higher emissions increase the likelihood of default. Scope 1 emissions, however, were not significant. Overall, the integration of carbon emissions into the model improves its predictive power, highlighting the importance of both financial stability and environmental impact in credit risk assessment.

Table 13: Summary of the logistic regression (Hypothesis 1)

	Dependent variable:			
	flag_default			
	(1)	(2)	(3)	(4)
Operating_CF_margin	-4.485^{***}	-4.544^{***}	-7.315^{***}	-3.949^{***}
	(1.177)	(1.188)	(1.579)	(1.332)
Operating_CF_ratio	-1.403^{***}	-1.399^{***}	-1.496^{***}	-1.819^{***}
	(0.251)	(0.251)	(0.316)	(0.289)
Equity_ratio	-2.774^{***}	-2.815^{***}	-4.183^{***}	-3.716^{***}
	(0.365)	(0.372)	(0.431)	(0.403)
Current_liabilities	-0.811^{***}	-0.836^{***}	-2.447^{***}	-2.441^{***}
	(0.149)	(0.157)	(0.284)	(0.263)
Scope_1_TotEm		0.064		
		(0.108)		
Scope_2_TotEm			1.140^{***}	
			(0.106)	
Scope_3_TotEm				1.325^{***}
				(0.132)
Constant	1.379^{***}	1.398^{***}	1.384^{***}	1.416^{***}
	(0.132)	(0.136)	(0.150)	(0.144)
Observations	1,437	1,437	1,437	1,437
Log Likelihood	−740.828	−740.655	−621.879	−673.215
Akaike Inf. Crit.	1,491.656	1,493.310	1,255.757	1,358.430
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Source: Authors

The VIF values, shown in Table 14, are below the multicollinearity threshold for all models. The transition risk variables used for Hypothesis 1 testing are the three scopes of carbon footprint, referred to as Scope 1, Scope 2, and Scope 3. The addition of transition risk variables did not significantly change the estimators of the standard model.

Table 14: Variance inflation factors (Hypothesis 1)

Model	CF margin	CF ratio	Equity ratio	Current liab	Emission var
(1)	2.429	2.478	1.046	1.022	
(2)	2.438	2.479	1.056	1.098	1.095
(3)	2.782	2.859	1.174	1.639	1.875
(4)	2.563	2.653	1.122	1.824	1.969

Source: Authors

7.1.2 Robustness check

Applying the climate-stressed models to the alternative data, the values and significance of the Scope 2 and Scope 3 estimators are consistent with the baseline results. There are no major changes in the values or significance of the standard model estimators, which would suggest multicollinearity (detail results are not reported in the paper but are available on request). The inclusion of Scope 2 and Scope 3 carbon footprints in the standard model improved its goodness of fit and produced robust, positive, and statistically significant estimators. This indicates that higher levels of Scope 2 and Scope 3 carbon emissions may drive defaults in the Bank. Therefore, Hypothesis 1 "Client's carbon footprint increases the odds of default on a SME loan in the Bank" cannot be rejected.

7.2 Hypothesis 2 testing

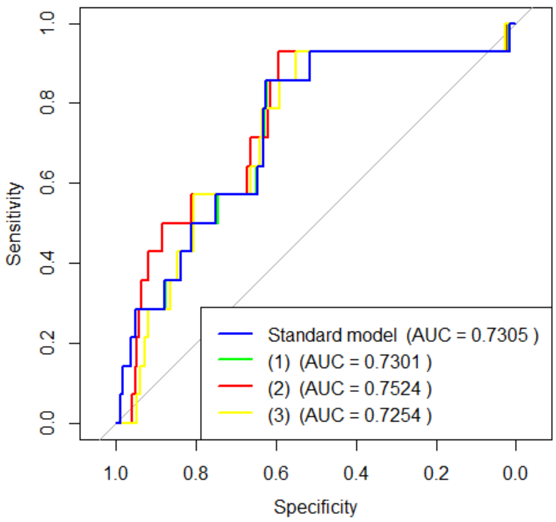
7.2.1 Baseline results

In testing Hypothesis 2, we evaluated the performance of standard and climate-stressed models in predicting credit defaults. Figure 5 illustrates that these models are moderately effective at ranking instances of default risk. This ranking capability is quantified by AUC score. Among the models, only Model (3), which incorporates Scope 2 emissions, achieved a higher AUC score compared to the standard model, indicating superior predictive performance.

Table 15 provides further insights into the models' effectiveness at a classification threshold of 0.5. At this threshold, all models demonstrated similar capabilities in detecting defaults, as evidenced by comparable performance metrics. However, Models (3) and (4) stood out by achieving higher sensitivity scores than the standard model. Sensitivity, or recall, measures the proportion of actual defaults correctly identified by the model. Higher sensitivity in Models (3) and (4) suggests these models are better at identifying potential defaults, making them more reliable for early warning systems in credit risk management.

In summary, while most models perform adequately in ranking and detecting defaults, incorporating climate-related variables such as Scope 2 emissions enhances the model's ability to identify defaults more accurately, thereby improving its practical utility in managing credit risk under climate-stressed conditions.

Figure 5: ROC curve (Hypothesis 2)



Source: Authors

Table 15: Performance evaluation (Hypothesis 2)

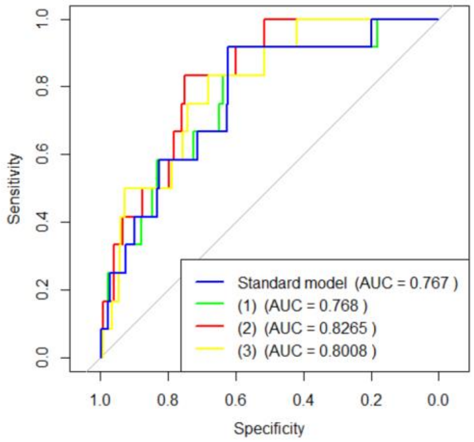
Model	TN	FN	TP	FP	Specificity	Sensitivity
Standard model	456	6	8	162	0.738	0.571
Model (2)	454	6	8	164	0.735	0.571
Model (3)	480	6	8	138	0.777	0.571
Model (4)	468	6	8	150	0.757	0.571

Source: Authors

7.2.2 Robustness check

Upon examining Figure 6, it is evident that all climate-stressed models demonstrated superior performance compared to the standard model, as indicated by higher AUC scores. The AUC is a critical metric that measures the model's ability to distinguish between default and non-default instances. Higher AUC scores signify better discriminative power of the climate-stressed models. Table 16 further supports these findings by showing that, at a threshold of 0.5, the climate-stressed models not only maintained higher sensitivity but also achieved better specificity rates. Sensitivity, or recall, refers to the model's ability to correctly identify true positive cases (defaults), while specificity measures the ability to correctly identify true negative cases (non-defaults).

Figure 6: ROC curve (Robustness check of Hypothesis 2)



Source: Authors

Table 16: Performance evaluation (Robustness check of Hypothesis 2)

Model	TN	FN	TP	FP	Specificity	Sensitivity
Standard Model	358	4	8	192	0.651	0.667
Model (2)	353	3	9	197	0.642	0.750
Model (3)	374	2	10	176	0.680	0.830
Model (4)	370	2	10	180	0.673	0.833

Source: Authors

Notably, Models (3) and (4) exhibited enhanced performance in both sensitivity and specificity compared to the standard model. This indicates that these models are more effective in accurately detecting defaults and correctly identifying non-defaults, thereby providing a more reliable and robust framework for credit risk assessment under climate-stressed conditions.

Model 3, stressed by the Scope 2 carbon footprint, achieved a higher AUC score magnitude on both data partitions. Additionally, it consistently demonstrated higher sensitivity and specificity rates compared to the standard model. The inclusion of the Scope 2 carbon footprint enhances the model's predictive power, and therefore, Hypothesis 2 "Inclusion of the client's carbon footprint increases the performance of the model for default prediction" cannot be rejected.

7.3 Hypothesis 3 testing

Table A. 2 summarizes the results of both the standard and climate-stressed models. The VIF values for all models, shown in *Table A. 3*, are below the threshold for multicollinearity, indicating that the predictor variables are not excessively correlated. For Hypothesis 3 testing, the transition risk variables included Scope 1, Scope 2, and Scope 3 financed carbon footprints. The inclusion of these transition risk variables did not significantly alter the estimators of the standard model, suggesting that the core relationships remain stable even after accounting for these additional factors. The estimators for Scope 1, Scope 2, and Scope 3 financed carbon footprints are both positive and statistically significant. When evaluating the models on imbalanced data, the effects of Scope 1 and Scope 2 emissions were slightly lower but still significant. These results highlight the significant impact of transition risks associated with carbon emissions on the likelihood of default, reinforcing the importance of incorporating environmental risk factors into credit risk assessments.

The robustness check results confirm that the estimators for Scope 1, Scope 2, and Scope 3 financed carbon footprints remain positive and statistically significant, even though their magnitudes have decreased. Additionally, the model does not exhibit multicollinearity issues. These findings suggest that higher levels of loan-financed emissions are associated with increased odds of default, thereby we cannot reject Hypothesis 3 "Client's financed carbon footprint increases the odds of default on a SME loan in the Bank". Although the detailed tables are not included here, they are available for review by interested readers. This also applies to the detailed results for Hypotheses 4-8.

7.4 Hypothesis 4 testing

The testing of Hypothesis 4 revealed that both standard and climate-stressed models perform moderately well in ranking instances of default risk. However, in terms of AUC, the climate-stressed models did not surpass the standard model. Additionally, when evaluated at a threshold of 0.5, none of the climate-stressed models exceeded the standard model in terms of sensitivity rate. This indicates that the standard model remains robust and effective in predicting defaults, even when compared to models incorporating climate stress factors.

The robustness check of the climate-stressed models using alternative data showed that the model stressed by the Scope 3 financed carbon footprint achieved a higher AUC than the standard model. At a threshold of 0.5, both the standard and climate-stressed models demonstrated improved accuracy in predicting defaults. However, when evaluating the performance on two differently adjusted data partitions, the climate-stressed models did not outperform the standard model in default prediction. This consistency across different data sets indicates that the standard model is robust and reliable. As a result, Hypothesis 4, which posited that climate-stressed models would perform better, can be rejected.

7.5 Hypothesis 5 testing

The summary of both standard and climate-stressed models indicates that all values of the VIF are below the multicollinearity threshold, suggesting no significant multicollinearity issues. The transition risk variables for Hypothesis 5 testing include Scope 1, Scope 2, and Scope 3 carbon intensities per unit of sales. The signs and significance of the estimators in the standard model remained consistent when transition risk variables were included, indicating robust results. All transition risk variables were found to be statistically significant.

The robustness check involved applying logistic regression models to alternative data. The results indicated no significant changes in the estimators of the standard predictors, maintaining their statistical significance. Both Scope 2 and Scope 3 carbon intensity estimators remained positive and statistically significant, closely aligning with the baseline results. The analysis confirmed no presence of multicollinearity. Two out of the three carbon intensity per unit of sales variables were positive and statistically significant in the climate-stressed models. These findings support the consistency and reliability of the baseline results, leading to the conclusion that Hypothesis 5 cannot be rejected.

7.6 Hypothesis 6 testing

In the testing of Hypothesis 6, both standard and climate-stressed models demonstrated moderate effectiveness in ranking instances of default risk. The models stressed by Scope 2 and Scope 3 carbon intensity per sales unit achieved higher AUC scores compared to the standard model, indicating better performance in distinguishing between defaults and non-defaults. However, when evaluated at a threshold of 0.5, none of the climate-stressed models outperformed the standard model in terms of sensitivity. Despite this, models (2) and (3) showed higher specificity, meaning they were better at correctly identifying non-default cases. These findings support the robustness of the climate-stressed models in certain aspects, although they did not surpass the standard model in all metrics.

The robustness check analysis for Hypothesis 6, using alternative data, revealed that all three climate-stressed models outperformed the standard model in terms of the AUC, indicating better overall ranking ability. At a threshold of 0.5, all models predicted the same or a higher number of defaults compared to the standard model. Notably, Models (3) and (4) achieved higher specificity, meaning they were more effective at correctly identifying non-default cases. Both Scope 2 and Scope 3 carbon intensity-stressed models consistently demonstrated higher AUC scores across different data partitions. Although these climate-stressed models did not surpass the standard model in default detection, they maintained the same sensitivity rate while achieving better specificity. Therefore, Hypothesis 6 “Inclusion of the client’s carbon intensity per unit of sales increases the performance of the model for default prediction” could not be rejected.

7.7 Hypothesis 7 testing

In the testing of Hypothesis 7, both standard and climate-stressed models were summarized, with values of the VIF indicating no multicollinearity issues. Transition risk variables, specifically Scope 1, Scope 2, and Scope 3 carbon intensities per asset, were utilized. The signs and significance of the estimators in the standard model remained consistent across all models. These findings support the relevance of carbon intensity metrics in evaluating default risk.

The robustness check evaluated the models using alternative data and found that all three transition risk variables (Scope 1, Scope 2, and Scope 3 carbon intensities per asset) remained statistically significant. Similarly, an increase in Scope 3 emissions per asset led to a 1% increase in the odds of default. The analysis indicated no issues with multicollinearity, as shown by the VIF. Both Scope 1 and Scope 2 carbon intensity per asset remained statistically significant across both balanced and imbalanced data using two different data partitions, with Scope 1 estimators being negative and Scope 2 estimators positive. Consequently, Hypothesis 7 “Client’s carbon intensity per earning asset increases the odds of default on a SME loan in the Bank” could not be rejected.

7.8 Hypothesis 8 testing

The testing of Hypothesis 8 revealed that both standard and climate-stressed models performed moderately well in predicting defaults. Model (3), which was stressed by Scope 2 carbon intensity per asset, achieved a higher AUC score, indicating better discriminatory ability compared to the standard model. Additionally, Model (3) demonstrated higher specificity and sensitivity, making it more effective at accurately identifying both defaults and non-defaults. These results suggest that incorporating Scope 2 carbon intensity into the model significantly enhances its predictive performance.

In the robustness check for Hypothesis 8, using alternative data, only Model (2), stressed by Scope 1 carbon intensity per asset, achieved a higher AUC score than the standard model. Model (2) also showed significantly higher sensitivity and specificity rates, indicating better performance in correctly identifying both defaults and non-defaults. Despite these results, none of the climate-stressed models, including Model (2), managed to consistently achieve a higher AUC or predict more defaults correctly across both sets of data. Consequently, these findings lead to the rejection of Hypothesis 8 “Inclusion of the client’s carbon intensity per earning asset increases the performance of the model for default prediction.”

7.9 Summary of results

In total, 8 hypotheses were tested throughout the study. Out of these, two hypotheses were rejected, while six could not be rejected. The hypotheses were divided into two main categories: those concerning the nature of the relationship between transition risk variables and the probability of default (Hypotheses 1, 3, 5 and 7), and those evaluating the contribution of transition risk variables to the overall model performance (Hypotheses 2, 4, 6 and 8). This bifurcation allowed for a comprehensive assessment of how transition risks influence credit risk predictions and the efficacy of incorporating these variables into predictive models.

Table 17 summarizes the partial hypotheses related to each transition risk variable for Hypotheses 1, 3, 5, and 7. When Scope 1 emissions were analyzed independently in climate-stressed models, the estimator was generally negative and statistically significant. This indicates that firms with direct emissions tend to have a lower PD, suggesting that these direct polluters are more stable according to the Bank's data. Conversely, increases in Scope 2 and Scope 3 carbon footprints typically resulted in a significant increase in the odds of default. The impact was particularly pronounced for Scope 2 emissions when considered independently in climate-stressed models, implying that firms with higher indirect emissions are more likely to default on loans. Additionally, firms utilizing indirect emissions in their production processes show a higher propensity to default compared to those accruing a carbon footprint primarily through their supply chain.

Table 17: Overview of the results (Hypotheses 1,3,5,7)

Independent variable	Results
Hypothesis 1: Not rejected	
Scope 1	Rejected
Scope 2	Not rejected
Scope 3	Not rejected
Hypothesis 3: Not rejected	
Scope 1,2	Not rejected
Scope 3	Not rejected
Hypothesis 5: Not rejected	
Scope 1	Rejected
Scope 2	Not rejected
Scope 3	Not rejected
Hypothesis 7: Not rejected	
Scope 1	Rejected
Scope 2	Not rejected
Scope 3	Rejected

Source: Authors

These findings align with the economic context of 2022, where the Czech Republic experienced soaring electricity and gas prices due to post-COVID demand and geopolitical tensions. Direct polluters (Scope 1) were less affected by these price hikes, either selling these commodities or having fixed prices. In contrast, Scope 2 polluters, who purchase these commodities at market prices, were significantly impacted. Scope 3 emitters may have experienced delayed effects as high energy costs took time to permeate through their supply chains.

While this situation might initially seem like a potential bias in the analysis, we interpret it as a proxy for a climate policy shock on the economy, which is likely to drive energy prices even higher. This interpretation aligns with the expectation of rising energy costs under stringent climate policies. The results are consistent with findings in academic literature (Capasso et al., 2020; Carbone et al., 2021), reinforcing the robustness of our conclusions.

Table 18 outlines the partial hypotheses related to each transition risk variable for Hypotheses 2, 4, 6, and 8. While these hypotheses serve a complementary role, several important findings emerged. All climate-stressed models demonstrated moderate performance in terms of discriminatory power, achieving a specificity rate above 0.5, which indicates that the majority of defaults were accurately predicted at a threshold of 0.5. Using two different random data partitions, we observed that incorporating the Scope 2 carbon footprint significantly enhanced the model's performance in terms of specificity, sensitivity, and the AUC-ROC curve magnitude. Additionally, adding Scope 2 and Scope 3 carbon intensity per sale to the standard model further improved its specificity rate and AUC-ROC curve magnitude. These results highlight the value of including specific climate-related variables to enhance the predictive accuracy of credit risk models.

Table 18: Overview of the results (Hypotheses 2,4,6,8)

Independent variable	Results
Hypothesis 2: Not rejected	
Scope 1	Rejected
Scope 2	Not rejected
Scope 3	Rejected
Hypothesis 4: Rejected	
Scope 1,2	Rejected
Scope 3	Rejected
Hypothesis 6: Not rejected	
Scope 1	Rejected
Scope 2	Not rejected
Scope 3	Not rejected
Hypothesis 8: Rejected	
Scope 1	Rejected
Scope 2	Rejected
Scope 3	Rejected

Source: Authors

7.10 Further research opportunities

We identify three key areas for further research related to this paper. First, using the same dataset, a climate stress test for the Bank could be conducted. This would involve analyzing and quantifying various future European climate policy scenarios and their direct impacts on the Bank's capital requirements. Second, as banks are increasingly pressured to support green finance, it is likely that more banks will start collecting similar emissions data from their clients, a practice that is becoming mandatory in some jurisdictions around the globe, such as under the EU's CSRD and the Task Force on Climate-related Financial Disclosures (TCFD) in the United Kingdom. This would enable researchers to compare the findings of this paper with those from different banks, allowing for a broader validation of results. Additionally, the availability of time-series data on client carbon footprints could facilitate more complex analyses. Third, this paper utilizes logistic regression, a straightforward and commonly used method for credit risk estimation. However, probit models or more sophisticated machine learning models often provide more precise results. Therefore, applying advanced machine learning techniques to address similar research questions could represent a valuable opportunity for further investigation. Fourth, building on the associations and causal relations identified in existing studies, further research could delve deeper into the underlying reasons why firms' carbon risk is positively correlated with their default risk, as highlighted by studies like Kabir et al. (2021). Investigating how specific factors such as regulatory changes, reputational damage, and carbon risk premiums directly contribute to this relationship, particularly for SMEs, could provide valuable insights. Finally, exploring the effectiveness of various carbon mitigation strategies in mitigating default risk could offer practical guidance for firms navigating the transition to a low-carbon economy.

8. Conclusion

This paper leverages a unique opportunity to analyze internal data collected by the Bank, which includes standard financial information as well as carbon footprint data for SME clients. Our contribution is four-fold. The primary contribution of this paper is the empirical evidence on the relationship between climate transition risk and credit risk. The analysis was structured as a stress test of a standard credit scoring model, with a set of transition risk variables added separately. Logistic regression was used for the climate-stress test, incorporating three scopes of carbon footprint, financed carbon footprint, and carbon intensity of the client. The findings reveal that Scope 1 emitters are generally less prone to credit default in the Bank, while Scope 2 and Scope 3 indirect emitters tend to default more. These findings are consistent with the economic conditions of 2022, during which the Czech Republic faced sharply rising electricity and gas prices driven by post-COVID demand and geopolitical tensions. Scope 1 emitters were relatively insulated from these price increases, as they either sold these commodities themselves or operated under fixed-price agreements. The level of Scope 2 and Scope 3 carbon footprint and carbon intensity was identified as a potential driver of default, consistent with the findings of Capasso et al. (2020), Carbone et al. (2021), Thornton et al. (2023) and Xinyu et al. (2023).

The second contribution is methodological, as the performance of the climate-stressed logistic regression models was observed and compared to the standard model. The inclusion of the Scope 2 carbon footprint in the credit scoring model improved its discriminatory power and ability to correctly predict credit defaults. Additionally, integrating Scope 2 and Scope 3 carbon intensity per unit of sales enhanced the model's ability to correctly predict non-defaults while maintaining the same accuracy in predicting defaults. This aligns with the research by Battiston et al. (2017) and Monasterolo et al. (2017), who highlighted the importance of incorporating climate risk factors into financial models. We are also demonstrating the value added by corporate climate disclosures, in terms of identifying risk.

The third contribution is the identification of four financial predictors that drive credit default. These indicators proved to be statistically significant, forming a standard model capable of detecting the majority of defaults in the testing data. The standard model predictors thus serve as an empirical cross-check on the data provided by the Bank. This finding supports the work of Jakubík & Teplý (2011) on credit scoring models. Finally, the paper offers a comprehensive summary of academic literature on climate transition risk in financial markets, effectively identifying a significant literature gap and suggesting further research opportunities, as noted by Dunz et al. (2019) and Dafermos & Nikolaidi (2021).

Finally, we contribute by leveraging the increasingly available disclosures on climate risk exposures, demonstrating how these disclosures can advance climate risk mitigation efforts while also enhancing banks' credit risk analysis. Additionally, we highlight the critical role of energy use in this context.

9. References

1. BCBS (2021). Climate-related risk drivers and their transmission channels.
2. Bartual Sanfeliu, C., F. García García, F. Guijarro, & A. Romero Civera (2012). Probability of deafault using the logit model: The impact of explanatory variable and data base selection. In “International Scientific Conference: Whither our Economics,” pp. 118–124. Mykolas Romeris University.
3. Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change, 7(4), 283-288.
4. Battiston, S., Y. Dafermos, & I. Monasterolo (2021). Climate risks and financial stability.
5. Bell, F. & G. van Vuuren (2022). The impact of climate risk on corporate credit risk. Cogent Economics & Finance, 10(1), 2148362.
6. Blasberg, A., R. Kiesel, & L. Taschini (2021). Climate default swap: Disentangling the exposure to transition risk through CDS.

7. Bruno, B., & Lombini, S. (2023). Climate transition risk and bank lending. Journal of Financial Research. https://doi.org/10.1111/jfir.12360
8. Capasso, G., Gianfrate, G., & Spinelli, M. (2020). Climate change and credit risk. Journal of Cleaner Production, 266, 121634.
9. Carbone, V., Moatti, V., & Vinzi, V. E. (2021). Assessing the impact of climate change on credit risk. Journal of Financial Stability, 53, 100773.
10. Chava, S. (2014). Environmental externalities and cost of capital. Management Science, 60(9), 2223–2247.
11. Cramer, J. (2003). Logit models from economics and other fields. Research Papers in Economics.
12. Dafermos, Y., & Nikolaidi, M. (2021). How can green differentiated capital requirements affect climate risks? A dynamic macrofinancial analysis. Journal of Financial Stability, 54, 100780.
13. Devalle, A. (2017). The linkage between ESG performance and credit ratings: A firm-level perspective analysis.
14. Ding, X., Ren, Y., Tan, W., & Wu, H. (2023). Does carbon emission of firms matter for bank loans decision? Evidence from China. International Review of Financial Analysis. https://doi.org/10.1016/j.irfa.2023.102556
15. Dombrovskis, V. (2018). Speech by Vice-President Valdis Dombrovskis at the High-Level Conference on Sustainable Finance. European Commission.
16. Douzas, G., F. Bacao, & F. Last (2018). Improving imbalanced learning through a heuristic oversampling method based on k-means and smote. Information sciences 465: pp. 1–20.
17. Dumitrescu, E., S. Hué, C. Hurlin, & S. Tokpavi (2022). Machine learning for credit scoring: Improving logistic regression with non-linear decision tree effects. European Journal of Operational Research, 297(3), 1178–1192.
18. Dunz, N., Naqvi, A., & Monasterolo, I. (2019). Climate Transition Risk, Climate Sentiments, and Financial Stability in a Stock-Flow Consistent Model. Journal of Economic Dynamics and Control, 106, 103783.
19. ECB (2020). Guide on climate-related and environmental risks, supervisory expectations relating to risk management and disclosure. European Central Bank.
20. European Commission. (2019). The European Green Deal. COM(2019) 640 final.
21. European Commission. (2022). Corporate Sustainability Reporting. Retrieved from https://ec.europa.eu.
22. Faralli, M. & F. Ruggiero (2022). The rise of climate risks: Evidence on firms' expected default frequencies. Available at SSRN 4144802.
23. Greene, W. H. (2003). Econometric analysis. Pearson Education India.
24. Hand, D., Henley, W. (1997). Statistical Classification Methods in Consumer Credit Scoring: A Review. Journal of the Royal Statistical Society, Vol. 160, No. 3, pp. 523–541.
25. Höck, A., C. Klein, A. Landau, & B. Zwergel (2020). The effect of environmental sustainability on credit risk. Journal of Asset Management, 21(2), 85–93.
26. Huljak, I., R. Martin, D. Moccero, & C. Pancaro (2022). Do nonperforming loans matter for bank lending and the business cycle in euro area countries? Journal of applied economics 25(1): pp. 1050–1080.
27. IPCC (2021). Weather and climate extreme events in a changing climate (chapter 11).
28. Ivančová, S. (2024). Climate risk in financial markets. Master thesis. Charles University. Czech Republic.
29. Ivanov, I., Rajan, U., & Zingales, L. (2023). Banking on carbon: Corporate lending and cap-and-trade policy. Review of Financial Studies, 37(5), 1640-1680. https://doi.org/10.1093/rfs/hhac068
30. Jakubík, P., & Teplý, P. (2011). The impact of macroeconomic factors on credit risk of loan portfolios. Prague Economic Papers, 20(1), 3-20.
31. Jung, J., K. Herbohn, & P. Clarkson (2018). Carbon risk, carbon risk awareness and the cost of debt financing. Journal of Business Ethics, 150, 1151–1171.

32. Kabir, M. N., Rahman, S., & Rahman, A. (2021). Carbon emissions and default risk: International evidence from firm-level data. Economic Modelling, 103, 105617. https://doi.org/10.1016/j.econmod.2021.105617
33. Kočenda, E., & Iwasaki, I. (2022). Bank survival around the World: A meta-analytic review. Journal of Economic Surveys, 36(1), 108-156.
34. Kotró, B. & M. Márkus (2020). The impact of ESG rating on corporate bond yields. Economy and Finance: English-Language Edition of Gazdaság és Pénzügy, 7(4), 474–488.
35. Leone, A. J., M. Minutti-Meza, & C. E. Wasley (2019). Influential observations and inference in accounting research. The Accounting Review 94(6): pp. 337–364.
36. Mays, E. (2001). Handbook of Credit Scoring, Chicago: Glenlake Publishing Company, Ltd.
37. Mohd, A., & Hishamuddin, M. S. (2024). Green financing and bank stability in ASEAN: The mediating role of climate risk. Asian Journal of Business and Accounting, 17(1), 45-68. https://doi.org/10.2139/ssrn.4174312
38. Monasterolo, I., Battiston, S., Janetos, A. C., & Zheng, Z. (2017). Vulnerable yet resilient: The impact of climate change on the global financial system. Environmental Science & Policy, 70, 3-15.
39. Nguyen, Q., I. Diaz-Rainey, & D. Kuruppuarachchi (2023). In search of climate distress risk. International Review of Financial Analysis, 85, 102444.
40. Nithi, S., Silvapulle, P., Gao, J., & Fenech, J.-P. (2021). Local logit regression for loan recovery rate. Journal of Banking and Finance, 126(5), 106093. https://doi.org/10.1016/J.JBANKFIN.2021.106093
41. Nordhaus, W. D. (2007). The challenge of global warming: Economic models and environmental policy, volume 4. Citeseer.
42. Ohlson, J. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, Vol. 18, No. 1, pp. 109–131.
43. Oikonomou, I., C. Brooks, & S. Pavelin (2014). The effects of corporate social performance on the cost of corporate debt and credit ratings. Financial Review, 49(1), 49–75.
44. Razuan, M., & Hishamuddin, A. (2024). Transformative impacts of green finance on CO2 emissions and bank stability. The European Proceedings of Social and Behavioural Sciences. https://doi.org/10.15405/epsbs.2024.05.30
45. Rosenberg, E., Gleit, A. (1994). Quantitative Methods in Credit Management: A Survey. Operations Research, Vol. 42, No. 4, pp. 589–613.
46. Sironi, A., Resti, A. (2007), Risk Management and Shareholders' Value in Banking. 1st Ed. New York: John Wiley & Sons.
47. Stern, N. (2009). Climate change, internationalism and India in the 21st century. CCCEP Policy Paper.
48. Stepankova, B., Teply, P. (2023). Consistency of Banks' Internal Probability of Default Estimates: Empirical Evidence from the COVID-19 Crisis. Journal of Banking and Finance. 106969, doi: https://doi.org/10.1016/j.jbankfin.2023.106969
49. Thornton, P., Ferri, G., & Lacitignola, P. (2023). The impact of the Paris Climate Agreement on default risk: Evidence from Italian firms. Journal of Banking & Finance, 147, 106689. https://doi.org/10.1016/j.jbankfin.2023.106689
50. Thornton, J., Altunbaş, Y., & Nobile, L. (2024). Credit risk and firm carbon emissions: A dynamic regression discontinuity approach. https://doi.org/10.2139/ssrn.4696214
51. United Nations (2015). PARIS AGREEMENT.
52. Wang, H.-J., Y. Geng, X.-Q. Xia, & Q.-J. Wang (2021). Impact of economic policy uncertainty on carbon emissions: Evidence from 137 multinational countries. International Journal of Environmental Research and Public Health, 19(1), 4.
53. World Bank (2020). World Bank's "State and Trends of Carbon Pricing 2020 report.
54. Xinyu, L., Zhang, W., & Zhou, Y. (2023). Carbon footprint and credit risk: Implications for banks' lending decisions. Energy Economics, 123, 106397. https://doi.org/10.1016/j.eneco.2023.106397

55. Zhang, Y., Y. Liu, & H. Wang (2023). How credit default swap market measures carbon risk. Environmental Science and Pollution Research, pp. 1–21.

10. Appendix

Table A. 1: Summary of the logistic regression (balanced data)

	Dependent variable: flag_default (1)	Dependent variable: flag_default (2)
Operating_CF_margin	-4.485^{***}	-4.201^{***}
	(1.177)	(1.142)
Operating_CF_ratio	-1.403^{***}	-1.621^{***}
	(0.251)	(0.256)
Current_liabilities	-0.811^{***}	-0.780^{***}
	(0.149)	(0.153)
Equity_ratio	-2.774^{***}	-2.108^{***}
	(0.365)	(0.381)
Debt_to_Assets		1.912^{***}
		(0.421)
Constant	1.379^{***}	0.566^{***}
	(0.132)	(0.213)
Observations	1,437	1,437
Log Likelihood	−740.828	−730.510
Akaike Inf. Crit.	1,491.656	1,473.019
Note:	*p<0.1; **p<0.05; ***p<0.01	

Source: Authors

Table A. 2: Summary of the logistic regression (Hypothesis 3)

	Dependent variable: flag_default (1)	(2)	(3)
Operating_CF_margin	-4.485^{***}	-4.424^{***}	-2.360^{*}
	(1.177)	(1.217)	(1.219)
Operating_CF_ratio	-1.403^{***}	-1.530^{***}	-2.124^{***}
	(0.251)	(0.260)	(0.288)
Equity_ratio	-2.774^{***}	-2.855^{***}	-2.402^{***}
	(0.365)	(0.370)	(0.379)
Current_liabilities	-0.811^{***}	-1.021^{***}	-1.650^{***}
	(0.149)	(0.165)	(0.212)
Fin_Scope12		0.530^{***}	
		(0.089)	
Fin_Scope3			1.022^{***}
			(0.084)
Constant	1.379^{***}	1.372^{***}	0.857^{***}
	(0.132)	(0.134)	(0.141)
Observations	1,437	1,437	1,437
Log Likelihood	−740.828	−721.030	−635.961
Akaike Inf. Crit.	1,491.656	1,454.060	1,283.923
Note:	*p<0.1; **p<0.05; ***p<0.01		

Source: Authors

Table A. 3: Variance inflation factors (Hypothesis 3)

Model	CF margin	CF ratio	Equity ratio	Current liab	Emission var
(1)	2.429	2.478	1.046	1.022	
(2)	2.377	2.441	1.049	1.191	1.188
(3)	2.397	2.562	1.043	1.422	1.560

Source: Authors