UNIVERSITY OF OXFORD
SMITH SCHOOL OF ENTERPRISE & ENVIRONMENT

Prudential Regulation and Transition Risk: Evidence from Bank Lending and Firm Emissions

Matteo Gasparini and Fulvia Marotta

15 September 2026

Oxford Smith School of Enterprise and the Environment | **Working Paper No. 26-03** ISSN 2732-4214 (Online)

The Smith School of Enterprise and the Environment (SSEE) was established with a benefaction by the Smith family in 2008 to tackle major environmental challenges by bringing public and private enterprise together with the University of Oxford's world-leading teaching and research. Our vision is to transform economies and governance so that people and nature can thrive together.

Research at the Smith School shapes business practices, government policy and strategies to achieve net-zero emissions and sustainable development. We offer innovative evidence-based solutions to the environmental challenges facing humanity over the coming decades. We apply expertise in teaching, economics, finance, business and law to tackle environmental and social challenges in six areas: water, climate, energy, nature, food and the regenerative economy.

SSEE has several significant external research partnerships and Business Fellows, bringing experts from industry, consulting firms, and related enterprises who seek to address major environmental challenges to the University of Oxford. We offer a variety of open enrolment and custom Executive Education programmes that cater to participants from all over the world. We also provide independent research and advice on environmental strategy, corporate governance, public policy and long-term innovation.

For more information on SSEE please visit: www.smithschool.ox.ac.uk

Suggested citation: Gasparini, M. and Marotta, F. (2026). "Prudential Regulation and Transition Risk: Evidence from Bank Lending and Firm Emissions." Smith School Working Paper 26-03.

Prudential Regulation and Transition Risk: Evidence from Bank Lending and Firm Emissions

Matteo Gasparini[1] and Fulvia Marotta[1, 2]

[1]Institute for New Economic Thinking, University of Oxford

[2]De Nederlandsche Bank

September 6, 2026

Abstract

We use Euro-area credit register data with firm-level carbon emissions to examine whether banks' internal models price transition risk and the downstream impacts on capital requirements and loan pricing. We do not find evidence that banks' internal models price transition risk, but rather the opposite. We find that firms with higher emissions are consistently assigned lower risk estimates than lower emissions ones, even within sectors. High-emitting sectors such as agriculture, electricity and oil and gas are found to have lower estimates of risk compared to other sectors while low-carbon firms in the electricity sector have higher estimates of risk. This implies that low-carbon borrowers face higher funding costs and higher capital requirements which may not be representative of the underlying transition risk.

Keywords: Climate Finance, Prudential Regulation, Financial Regulation

JEL codes: G21, G28, Q54, Q58, E58

The views expressed in this paper are solely those of the author and do not necessarily reflect those of De Nederlandsche Bank or any other affiliated institution. Fulvia Marotta is also an Honorary Research Associate at the Smith School of Enterprise and the Environment, University of Oxford. The authors gratefully acknowledges discussions and feedback from colleagues at the Smith School and other institutions, particularly Sam Fankhauser, Irene Monasterolo, Peter Tufano, Maurice Bun, and Bas ter Weel.

1 Introduction

A growing literature shows that the risks arising from a transition to net-zero carbon emissions - or transition risks - are financially material and affect asset prices, portfolio choices, and corporate financing conditions (Giglio et al., 2021; Edmans and Kacperczyk, 2022; Gasparini and Tufano, 2023). Yet, while there is some evidence that financial markets appear to price transition risk, the evidence on the less transparent, regulatory-driven, banking market remains limited. Corporate loans represent a large share of global financing and are mostly priced through banks' internal models. Under Basel Pillar I capital requirements, lenders must use internal models to estimate borrowers' credit risk to set aside capital and to price loans. However, these models use historical financial information which may not be capturing long-term, uncertain, and forward-looking risks such as transition risks - despite being a key factor in how resources are allocated.

We study whether lenders' internal models price transition risks with a granular administrative dataset of lender-borrower relationships. We analyze the relationship between borrower-level carbon emissions and lenders' internal models estimate of borrowers credit risk. We merge data from the European Central Bank's AnaCredit database, which provides detailed lender–borrower relationships and lenders' probability-of-default (PD) estimates, with firm-level financial information from Bureau van Dijk's Orbis and carbon emissions data from S&P Trucost. The resulting panel covers over 7000 borrowers and over 100 lenders across the Euro Area between 2019 and 2024. These data allow us to investigate how lenders' internal models estimates vary with borrowers' exposure to transition risk - as proxied by carbon emissions[1].

We do not find evidence that lenders' internal models price transition risk, but rather the opposite. We show that lenders' internal models assign high-carbon borrowers (in terms of Scope 1 and Scope 3 emissions) lower estimates of risk than low-carbon borrowers. The negative relationship between emissions and risk estimates is robust across different specifications and persists both across and within sectors. This indicates that not only high-emission industries, but also relatively higher-emitting firms within the

1 Specifically we use lenders' estimates of Probability of Default (PD) which represent an assessment of borrowers' credit risk.

same industry, are assessed as less risky. We also document that high-carbon borrowers face lower loan spreads, suggesting that internal risk assessments may not only affect capital requirements, but also loan pricing and potentially capital allocation. While part of this relationship is explained by differences in observable financial fundamentals — such as profitability, size, and return on equity — the effect remains statistically significant after controlling for standard risk drivers[2]. In economic terms, a one-standard-deviation increase in a borrower's carbon emissions is associated with a 3.6–4.8% lower Probability of Default estimate and 8.3–10.7% lower loan spreads.

We are explicit throughout that our estimates are not causal but correlational: emissions are not randomly assigned, and we do not observe a firm-level shock to emissions that is plausibly unrelated to a firm's broader financial trajectory. A correlational reading is, however, sufficient for our purposes. Capital requirements and, by regulatory design, loan pricing are built directly on the risk estimates that banks' models produce; documenting how those estimates vary with borrower emissions is informative about the current functioning of the regulatory framework. Nor do we claim that banks' assessments are wrong in an ex-post sense: transition risk has not yet been realised, so no default-outcome test is available. It is indeed not possible to assess whether banks' estimates are not accurate, but we can understand whether transition risk is factored-in or not in these assessments which by itself carries important implications in terms of loan pricing and possibly capital allocation.

A possible explanation for our results may reside in the capital requirements framework reliance on historical experience and borrower-specific differences in the financial structure of low-carbon and high-carbon borrowers, especially in the energy sector. Model-based credit risk assessments rely heavily on historical default experience and borrower financial characteristics. High emissions firms, especially in sectors such as energy, utilities, and heavy industry, often have large tangible asset bases, established cash flows, and long lending relationships. We show that these characteristics reduce estimates of credit risk in standard models, even if they may increase exposure to future transition risk. However, we acknowledge other factors (e.g., banks' relationship, analysts' expec-

2 It should be noted that differently from prior literature (Delis et al., 2024; Altavilla et al., 2024), our objective is not to compare firms conditional on the same risk profile, but to show how risk profiles may be - correctly or not - different between low-and high-carbon firms.

tations) may also influence our results. Qualitative adjustments based on "soft-factors" are oftentimes considered in internal models - especially for larger firms such as those in our sample.

Differently from previous literature, the main mechanism we try to characterise is mechanical rather than behavioural. Banks' internal models, unlike other pricing models, must demonstrate their discriminatory power against realised defaults over the bank's historical observation window (Behn et al., 2022; Plosser and Santos, 2018). Because carbon prices have remained below transition-consistent levels, a risk driver capturing transition exposure would have little to no realised discriminatory power in that window. Hence internal models mostly rely on determinants of realised default risk and coincidentally the dimensions that high-carbon incumbents tend to score favourably relative to smaller, more leveraged, low-carbon entrants. The negative association we document is thus consistent with models pricing the risk drivers they are designed and validated to use to survive supervisory scrutiny, rather than with banks behaviourally favouring high-carbon borrowers.

This paper makes three primary contributions. First, we provide micro-level evidence on whether banks' internal models price transition risk. While most existing evidence on transition risk and bank lending is inferred from prices and quantities (e.g., Delis et al. (2024)), our data reports the PD that each bank assigns to each borrower, allowing us to examine the risk assessment directly rather than through its downstream consequences. Contrary to broader financial markets, banks do not seem to price transition risk: whereas a growing literature documents that higher-emitting firms command a premium in equity and bond markets (Bolton and Kacperczyk, 2021, 2023; Giglio et al., 2021), we find that lenders' internal models assign systematically lower probabilities of default to higher-emitting borrowers, both across and within sectors. We discuss how this could be a mechanical consequence of the regulation and the financial structure of low and high-carbon firms rather than a behavioural factor.

Second, we provide empirical evidence that Pillar I capital requirements may not fully internalise transition risk suggesting that the banking sector could be exposed to financial risks that are not captured by the current regulatory framework. A growing body of evidence suggests that transition risk is financially material and affects credit risk

(Carbone et al., 2025; Seltzer et al., 2022), yet our results indicate that banks' internal models do not currently reflect this. From a policy perspective, our findings underscore that incorporating long-term forward-looking assessments into the prudential frameworks may be beneficial.

Third, our study contributes to the debate on green capital requirements. While green capital requirements explicitly designed to foster the green transition may raise legitimate concerns about the scope of prudential regulation[3] or not be a good substitute to carbon taxation (Oehmke and Opp, 2025), if transition risk is material, the current framework may penalise the financing of low-carbon borrowers relative to high-carbon ones[4]. A back-of-the-envelope calculation suggests that this effect operates mainly on the quantity, rather than the price, of low-carbon investment. For example, energy borrowers at the 10th versus 90th percentile of emissions face a spread differential of roughly 20–30 basis points, which translates into a levelised-cost of electricity (LCOE) increase of only roughly 1–2% for the lower-emissions company's project relative to the higher-emissions one[5]. This suggests that the macroeconomic effect may be mostly through a reduction of deployment of low-carbon energy rather than a negative effect on energy prices.

The study most closely related to ours is Altavilla et al. (2024), which - opposite to us - document that Euro-area banks charge higher interest rates to high-emission firms. Our results differ in that they are not conditional on the probability of default and therefore do not restrict the analysis to borrowers with comparable ex-ante risk. Instead, we show that low-carbon firms tend to be assessed as riskier by banks and, as a consequence, receive higher interest rates and we discuss a possible reason for our findings that is grounded in the design of the regulatory framework itself.

3 Only financial stability objectives are currently included in most financial supervisors and regulators mandates.

4 As discussed in Gasparini et al. (2024).

5 Based on the coefficients on log Scope 1 and Scope 3 emissions in the spread regressions of Table 8 (columns without controls), converted into basis points under the assumption that the borrower-level standard deviation of the spread is 80–160 basis points (not separately reported for the estimation sample) and that the 10th and 90th percentiles of log emissions are 2.56 standard deviations apart (i.e., that log emissions are approximately normally distributed). The levelised-cost effect applies the resulting spread differential to the financing cost of a representative European utility-scale solar or onshore wind project, assuming a 70% debt share and a 6% baseline cost of capital, together with standard technology cost and capacity-factor assumptions for each. All figures in this footnote are illustrative calibrations rather than directly estimated quantities; the corresponding differential in assigned probabilities of default is reported in Table 3.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on prudential regulation and provides the institutional background. Section 3 describes the data sources and our methods. Section 4 presents the main results. The final section concludes.

2 Related Literature and Institutional Background

The financial system plays a fundamental role in modern economies by channelling capital from savers to borrowers, thereby supporting investment, consumption, and long-term economic development. A well-functioning financial system is essential for macroeconomic stability; disruptions in credit markets can have negative consequences for households and firms, as evidenced by the various - recent and less recent - financial crises (Bernanke and Gertler, 1990; Bernanke, 2023). Financial intermediation, a core function of the banking sector, reduces information asymmetries and monitoring costs, enabling more efficient capital allocation (Diamond, 1984). However, it is also subject to agency problems, particularly moral hazard, which can incentivize excessive risk-taking and contribute to financial instability (Hellmann et al., 2000; Goodhart et al., 2012). In response to these vulnerabilities, prudential regulation has been progressively introduced and strengthened over recent decades to enhance the resilience of the financial system.

Prudential regulation encompasses a set of rules and supervisory practices aimed at ensuring the resilience of the financial system and correcting the market failures. At its core is the Basel capital framework, developed by the Basel Committee on Banking Supervision (BCBS), which sets international standards for capital adequacy, liquidity, and risk management. While national regulators retain discretion to tailor these rules, such as the SME supporting factor in the European Union, the Basel framework provides the foundation for most regulatory regimes. A central component of this framework are Pillar I requirements which mandate banks to hold capital in proportion to the estimated riskiness of their assets, typically measured through Risk-Weighted Assets (RWA). These risk weights are calculated using either standardized approaches or internal models, such as the Internal Ratings-Based (IRB) and Advanced IRB approaches, which allow banks to estimate key risk parameters (e.g., the probability of default) with internal models based on historical data (Dewatripont and Tirole, 1994).

IRB models are not estimated freely: risk drivers must be supported by empirical evidence of their ability to discriminate between defaulting and non-defaulting borrowers over a historical observation period, and models are subject to ongoing supervisory validation and backtesting against realised outcomes. A related literature shows that this reliance on historical, validated estimation is not without cost. Behn et al. (2022) show that model-based capital regulation led banks to systematically underestimate risk on the exposures for which internal models were used, relative to a standardized benchmark. Plosser and Santos (2018) document that internal ratings for economically similar borrowers can differ substantially across banks. This literature is generally concerned with risks that have already been experienced, at least by some banks, at some point in the historical record.

The macroeconomic implications of capital requirements have been widely debated since early theoretical work modelling how capital adequacy rules shape banks' portfolio and risk-taking decisions (Crouhy and Galai, 1986; Rochet, 1992; Blum and Hellwig, 1995). One strand of the literature argues that higher capital requirements enhance financial stability by incentivizing better monitoring, improving bank valuations, and reducing the likelihood of crises (Holmström and Tirole, 1997; Mehran and Thakor, 2011; Allen et al., 2011; Admati and Hellwig, 2013; Thakor, 2014; Myerson, 2014). In contrast, others contend that stricter capital rules may reduce credit supply, increase the cost of financial intermediation, and lead to inefficient capital allocation (Diamond and Rajan, 2001; Baker and Wurgler, 2015). Some recent empirical studies have shown that changes in capital requirements can significantly affect banks' behavior (Behn et al., 2016; Fraisse et al., 2020; Jiménez et al., 2017; Bednarek et al., 2025). For instance, Gropp et al. (2019) find that the implementation of Basel III, which raised the minimum CET1 capital ratio from 5% to 9%, led to a contraction in bank lending and a reduction in RWAs. Similarly, Benetton et al. (2021) show that lower capital requirements are associated with reduced mortgage interest rates, showing the real effects on credit markets.

A recent strand of work has also examined how banks price the risk of a transition to net-zero carbon emissions or transition risk (de Bandt et al., 2025; Giglio et al., 2021; Edmans and Kacperczyk, 2022). For example, Delis et al. (2024) use syndicated loan data to show that banks charge higher spreads to fossil fuel firms with larger reserves, especially after the Paris Agreement, consistent with transition risks being priced into lending conditions. Similarly, Altavilla et al. (2024) use Euro area credit register data and document that higher borrower emissions intensity is associated with higher loan spreads. Ehlers et al. (2022) similarly find that syndicated loan spreads reflect a borrower-specific carbon risk premium tied to firms' own emissions trajectories, rather than to sector membership alone.

This pricing is not uniform across debt markets: Beyene et al. (2021) show that bond investors price the risk that fossil fuel firms' assets become stranded, while banks in the syndicated loan market largely do not. Using a setting in which transition risk is realised through policy rather than merely anticipated, Ivanov et al. (2024) exploit California's cap-and-trade programme and find that banks reduce lending to regulated high-emission firms once carbon pricing is introduced, suggesting that lenders can respond to transition risk when its materialisation is no longer purely prospective.

Taken together, this evidence suggests that higher emissions and greater transition risk are generally associated with higher financing costs, at least once transition risk begins to be realised. Yet, these studies primarily rely on market-based indicators such as loan spreads, bond yields, credit quantities, or systemic risk measures. Much less is known about how climate-related risks are incorporated into banks' internal risk models. This is relevant as those models play a central role in prudential regulation and in determining capital requirements and oftentimes loan prices.

It is also unclear whether the current design of prudential regulations is apt to mitigating transition risks in the financial system. This has been recently recognized as a critical objective among many central banks and financial supervisors worldwide. Recent policy proposals have suggested modifying capital requirements to support green investments, such as introducing a "green supporting factor" or a "brown penalizing factor" (Campiglio et al., 2018). Oehmke and Opp (2025) explore whether differentiated capital requirements could simultaneously promote financial stability and climate goals. They argue that while such tools may help internalize climate-related risks, but their effectiveness in redirecting capital flows toward green investments remains uncertain[6].

6 Relatedly, but in the context of monetary policy, Papoutsi et al. (2021) find that the European Central

The policy debate has increasingly recognized this concern. Regulatory bodies such as the European Central Bank (ECB) and the European Banking Authority (EBA) have emphasized the need for institutions to adapt their risk management practices to account for climate-related and environmental risks. The ECB, for instance, mandates that, where such risks are deemed relevant and material, they must be incorporated into the internal models used for calculating own funds requirements for credit and market risk.[7] Similarly, the EBA has outlined a phased approach recommending the inclusion of environmental and social risks in rating assignments and risk quantification processes, while advocating the medium- to long-term reassessment of risk drivers and the recalibration of Probability of Default (PD) and Loss Given Default (LGD) estimates.[8] Yet little evidence is present to show whether and to what extent banks internal models price transition risk. This paper aims to provide some empirical evidence on banks' internal models pricing of transition risk.

3 Methods

This section describes the data we use for our empirical analysis and the empirical specifications. We are mainly interested in the relationship between borrower-level carbon emissions – as our main proxy for transition risk – and lenders' estimates of borrower-level Probability of Default (PD) – as the main output of banks' internal models. Risk assessments in turn affect capital requirements and borrowers' cost of credit (i.e., lenders charge higher interest rates to borrowers with higher PDs) and possibly access to finance. We also test alternative specifications using dummies at sectoral level, ESG ratings, and the presence of decarbonization targets (among borrowers).

3.1 Data

The starting point for our data is the administrative dataset from the European Central Bank (ECB) AnaCredit. AnaCredit collects detailed information on virtually all banks in

Bank's corporate bond purchase program disproportionately favored high-emitting firms due to the structure of the bond market and the ECB's market neutrality principle

7 European Central Bank (2020).

8 European Banking Authority (2023).

the Euro area and their outstanding lending to borrowers. It provides granular data on the lender-borrower relationships including loan characteristics such as Loan to Value (LTV), Maturity, and outstanding amount (ONA). AnaCredit also provides banks' (lenders') estimates of the Probability of Default (PD) of clients, which are estimated using the Internal Rating Based Approach (IRB) models. We use the Instrument, Debtor, and Creditor tables of AnaCredit and group the information at lender-borrower level (creditor-debtor relationship) by summing the outstanding amount and averaging the Probability of Default and other variables at lender-borrower level.

We complement our data with borrowers' financial information from Bureau van Dijk's Orbis and carbon emissions from S&P's Trucost. Identifiers across sources are matched in two steps. First, AnaCredit debtor identifiers are linked to Orbis BvD IDs using the matching procedure developed by the European Central Bank (for Italy, France, and Spain we use the Codice Fiscale, SIREN code, and NIF, respectively, while for Germany we use the trade register number). Second, Orbis BvD IDs are matched to Trucost institution IDs using the Capital IQ fuzzy matching procedure, which relies on either exact company name matches or ISIN code matches; in most cases this yields a perfect name match, and the remaining imperfect matches are manually reviewed. As a consequence, the sample is limited to approximately 11,000 companies, corresponding to those matched with Trucost (i.e., only firms for which emissions data are available).

Our data has a total of 88974 lender-borrower relationships corresponding to 104 lenders and 7725 borrowers. Of the around 11000 firms matched between Orbis and Trucost, we are able to match around 9000 with AnaCredit. While most borrowers are associated with a small number of lenders in a given year, the distribution of lender relationships per borrower–year is highly skewed, with a subset of firms connected to many banks simultaneously. Moreover, borrower characteristics–including financial variables and carbon emissions–vary at the borrower–year level, whereas PDs are reported separately by each lender for the same borrower–year, resulting in systematic within–borrower variation in PD assignment across lenders.

After the matching, we apply two filters to ensure our sample is robust for our analysis. First, we restrict our sample only to banks with total assets as of 2023 above 10 EURbn.

This is meant to avoid smaller banks which mostly use the standardized approach[9]. The second filter is to ensure that each bank in our sample has at least 20 firms with carbon emissions every year. This is because smaller borrowers may not be captured in S&P's Trucost. Our final dataset is a panel of lender-borrower-year and 7725 borrowers and covers from January 2019 to December 2024 for a total of 6 years. We select this period because only from 2019 data from Anacredit is deemed comprehensive[10]. Table 1, provides some descriptive statistics. Additional details on sample construction, variable definitions, and descriptive statistics are provided in Appendix A.

3.2 Empirical Specification

We begin by examining the relationship between firm-level (borrower-level) carbon emissions and the lenders' estimates of borrower-level Probability of Default (PD)[11]. Our main empirical specification focuses on estimating the correlation between banks' estimates of borrower-level PDs and borrower-level emissions. Emissions vary at the borrower–year level, while PDs are assigned by banks to each borrower through their internal rating models. Since these models can differ across institutions and evolve over time, we include lender and year fixed effects to control for lender-specific modeling practices and time-specific macroeconomic conditions. This specification therefore exploits within-year, within-lender variation in PDs across borrowers. Formally, we estimate the following model:

$$PD_{i,l,t} = \lambda_l + \delta_t + \beta_1 \cdot Emissions_{i,t} + \varepsilon_{i,l,t}, \tag{1}$$

where $PD_{i,l,t}$ denotes the Probability of Default assigned to borrower i by lender l in year t. The term λ_l captures lender fixed effects, while δ_t denotes year fixed effects. The

9 The standardized approach is a simplified methodology to estimate capital requirements without relying on banks' internal models. Because smaller banks typically lack the economies of scale needed to build and maintain Internal Ratings-Based (IRB) models, they tend to rely on the standardized approach instead, which in turn results in higher average capital requirements.
10 See Molyneux et al. (2020)
11 The reader should note that other factors – such as Loss Given Default (LGD) – are considered in the regulatory formula for the calculation of Risk Weights (RWs). However, the assessment of borrowers' creditworthiness with the PD is generally one of the main drivers. This is important because, in turn, capital requirements affect the interest rate applied to borrowers (see Figure 1)

coefficient β_1 captures the association between borrower emissions and the PD assigned by the same lender in the same year, comparing borrowers with different emission levels.

The variable $Emissions_{i,t}$ measures the carbon profile of borrower i in year t and varies at the borrower–year level, while PDs are reported separately by each lender for the same borrower–year. In the baseline specification, $Emissions_{i,t}$ is measured as log carbon emissions, focusing in turn on Scope 1 and Scope 3 emissions. Scope 1 emissions capture direct greenhouse gas emissions from sources owned or controlled by the firm, while Scope 3 emissions reflect indirect emissions generated along the firm's value chain.[12] Finally, $\varepsilon_{i,l,t}$ is an idiosyncratic error term. Standard errors are clustered at the creditor–debtor (bank–firm) level to allow for arbitrary correlation in unobserved risk components within lending relationships over time.

Given the strong right-skewness of firm-level carbon emissions and the presence of firms with very small or zero reported values, we measure borrower emissions in logarithmic form in the baseline specification. Log transformations reduce the influence of extreme observations and allow for potential non-linearities in the relationship between emissions and credit risk, while preserving the relative ranking of firms by their carbon footprint.

A salient feature of the data is that some borrowers maintain credit relationships with multiple lenders within the same year, implying that the same borrower–year observation can appear repeatedly across lender relationships. To avoid a small number of highly connected borrowers disproportionately influencing estimation and inference, we cap the number of lender relationships per borrower–year in the baseline specification, restricting the sample to observations with at most five concurrent lenders. Appendix A documents the distribution of lender relationships.

To mitigate concerns about omitted variable bias – particularly the possibility that firm-level emissions are correlated with other financial characteristics that also influence PD assessments – we extend the baseline specification by including standard borrower-level controls such as size, profitability, and leverage. These controls aim to capture

12 Results using Scope 2 emissions are qualitatively similar to those reported for Scope 1 and Scope 3 emissions and are omitted for brevity. We do not estimate specifications using emission-intensity measures because scaling emissions by revenues or assets introduces a mechanical relationship with several borrower characteristics included as controls, such as firm size and profitability, complicating the interpretation of the estimated coefficients.

observable dimensions of a firm's risk profile that banks may already factor into their internal models. However, these richer fixed-effects structures come at a cost: they reduce the usable variation in the data and limit comparability across firms. Throughout, we emphasize transparency in these trade-offs and maintain a focus on simple, interpretable designs grounded in the available variation. In addition, we consider alternative fixed-effects specifications. This approach allows us to isolate within-firm changes in emissions and their association with changes in PDs over time, while absorbing all time-invariant heterogeneity at the firm level.

To further explore the relationship between capital requirements and borrower-level emissions, we enrich our baseline model by introducing industry fixed effects based on the NACE classification. This allows us to distinguish whether lenders assign higher PDs to borrowers with high emissions relative to other borrowers in the same industry (i.e., within-sector carbon intensity), or simply relative to firms in high-emitting industries (i.e., between-sector risk differentiation). The distinction is crucial for assessing whether the regulatory system is sensitive to a firm's relative environmental performance, or whether it disproportionately targets certain sectors regardless of firm-level transition risk.

Finally, we adopt alternative classifications of high- versus low-emitting borrowers. First, following Giannetti et al. (2026), we define high-emitting firms as those operating in industries falling within the top quintile of sector-level emissions, and low-emitting firms as those in the bottom quintile, using industry-level GHG emission data from Eurostat. This approach identifies firms based on the average carbon intensity of their sectoral activities. Second, we incorporate firm-level ESG metrics, specifically the environmental pillar scores provided by MSCI. MSCI's score captures firms' exposure to environmental risks, including physical and transition risks. These alternative measures allow us to assess the robustness of our results across different conceptions of environmental risk and performance.

We assess the robustness of our findings along several dimensions. In particular, we examine alternative sample definitions and trimming thresholds for the number of lender relationships per borrower–year; different clustering schemes for standard errors; alternative fixed-effects structures; Detailed results from these robustness analyses, together with additional descriptive statistics and data construction details, are reported in Appendix

A and B.

4 Results

We start by providing a descriptive analysis of the drivers of the estimates of the Probability of Default (PD). Table 2, reports the results from the regressions of banks' PD estimates on borrowers' financial characteristics. Firms with weaker financial performance—particularly lower profitability, smaller size and weaker capitalisation—are associated with higher probabilities of default. Specifically, Table 2, shows negative and statistically significant coefficients on earnings before interest and taxes as a percentage of operating revenue (ETMA), total assets (TOAS), return on assets (ROA), shareholders' funds as a percentage of total assets (SOLR) and firm age, indicating that larger, more profitable and better-capitalised firms tend to receive lower PDs, although the coefficient on cash flow as a percentage of operating revenue (CFOP) is small and not statistically significant in most specifications. We also find some country-level differences with France and Spain exhibiting higher average PDs than Germany and Italy. These results are broadly consistent with anecdotal evidence on the inputs used by banks in internal models and provide descriptive evidence on some of the financial drivers of PDs.

Before turning to the regression analysis, Figure 1 provides a visual overview of the main relationships explored in the paper. Panel A shows a strong positive relationship between borrowers' estimated Probability of Default and loan spreads, consistent with risk assessments being reflected in loan pricing. Panels B and C show that higher-emitting borrowers tend to have lower estimated probabilities of default and lower loan spreads, respectively.

In our main empirical specification, we run a regression between lenders' estimate of borrowers' Probability of Default (PD) and borrowers' log carbon emissions. We test different combinations of this relationship and focus on the results without controlling for any firm-specific characteristics first and then turn to an analysis controlling for borrowers' financial characteristics. This allows us to study whether any relationship emerges either as a result of the output of the models or because of intrinsic differences in financial characteristics used as inputs to the models. We then test this relationship with and without the borrower's sector fixed effects. This is important because it allows us to differentiate between firms with activities in more/less emitting sectors (e.g., Oil and Gas) and firms with the highest emissions within their sector (e.g., Renewable energy, Coal electricity generation) and test alternative hypotheses.

Differently from prior literature (Delis et al., 2024; Altavilla et al., 2024), our objective is not to compare firms conditional on the same risk profile, but to show how risk profiles may be different between low-and high-carbon firms. It is arguably difficult to take an "ex ante" view on whether these estimates are correct or not but differences in risk assessments shed light on internal models' risk profile assessments and banks' pricing of transition risk. These results allow us to discuss broader implications on how banks price loans and set aside capital requirements rather than an ideal experiment comparing two firms with exactly the same risk profile, besides emissions, that are borrowing from the same lender.

Throughout, we treat these patterns as correlational rather than causal: emissions are not randomly assigned across borrowers, and no firm-level shock to emissions plausibly unconnected to a firm's broader financial trajectory is available to us. A correlational reading is nonetheless sufficient for our purposes, since both capital requirements and, by regulatory design, loan pricing are built directly on the risk estimates that banks' models generate; documenting how those estimates co-move with borrower emissions is therefore informative about how the regulatory framework currently functions. Nor do we suggest that banks' assessments are mistaken with hindsight – transition risk has not yet materialised, so no realised-default test of accuracy exists. What our approach can speak to is not whether banks' estimates are right or wrong, but whether transition risk is being incorporated into these assessments at all, a question with its own material consequences for loan pricing and capital allocation.

In Panel A of Table 3, we show a negative and statistically significant relationship between borrowers' Scope 1 emissions and lenders' estimates of borrowers' Probability of Default (PD). Borrowers with log Scope 1 emissions one standard deviation higher (lower) than the mean are assigned a PD 3.6% lower (higher) on average (Panel A: Column 1). We also use Scope 3 emissions because representing the largest source of emissions of firms[13].

13 Scope 3 emissions often accounting for between 70% and 90% of all emissions. See UN Global Compact

In Table 3, we find consistent and statistically significant results for Scope 3 emissions. Borrowers with log scope 3 carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 4.5% lower (higher) by lenders (Panel B: Column 1). Note that these are results without controlling for any firm (borrower)-specific characteristics. This indicates that banks (lenders) tend to assess as riskier (less risky) firms with lower (higher) scope 1 and Scope 3 carbon emissions, on average.

We then study whether these differences in risk assessments arise from borrower-specific factors of low- and high-carbon borrowers that lenders' models accurately capture, or from other reasons. Specifically, our results could reflect one of two possible hypotheses: (1) there is no difference in risk between low/high-carbon borrowers but lenders do not assess it correctly and 2) there is a difference between low/high-carbon borrowers and lenders assess it correctly. If the first hypothesis is true, it suggests that banks' internal risk models may not price transition risk. If the second is true, then the observed outcomes may simply reflect underlying structural differences in the financial creditworthiness of these firms. Operationally, we run the same regression controlling for some common financial characteristics of firms which drive PD estimates such as earnings before interest and taxes as a percentage of operating revenue (ETMA), total assets (TOAS), return on assets (ROA), shareholders' funds as a percentage of total assets (SOLR), and firm age.

In Table 3, we show that the coefficient remains negative and statistically significant when controlling for firm characteristics for both Scope 1 (Panel A: Column 2) and Scope 3 (Panel B: Column 2) emissions, although the magnitude of the effect diminishes. Borrowers with Scope 3 carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 2.6% lower (higher) by lenders on average. Similarly, borrowers with Scope 1 emissions one standard deviation higher than the mean are assigned a PD 2% lower. This suggests that borrower-specific characteristics could explain part of the negative relationship between carbon emissions and PD, but other factors may be at play. For example, standard financial characteristics are inherently backward-looking and may not reflect firms' exposure to forward-looking transition risks or lenders rely on unobserved soft information — such as client relationships or qualitative assessments — that is not captured by our set of controls. Regardless of the reason, our results suggest banks' internal models do not price transition risk also when controlling for common financial ratios[14].

These patterns are also visible non-parametrically. Figure 3 plots average PDs across quintiles of firms' emission intensity. Borrowers in the lowest emission-intensity quintile are associated with higher average PDs than borrowers in the highest quintile, providing a visual illustration of the negative association between emissions and risk assessments documented in Table 3.

A related question of interest concerns the relationship between credit risk assessments and firms' emission profiles relative to their sector peers. While some sectors — such as Oil and Gas, Electricity, and Transport — are high-emitting overall and others are low-emitting, meaningful heterogeneity persists within individual sectors. The Power Generation sector, for example, is high-emitting on average, yet encompasses both low-emission renewable energy producers and high-emission coal producers. Disentangling within-sector variation is important for identifying the mechanism underlying our main result: it allows us to assess whether banks' internal models fail to price transition risk because they are agnostic to differences in economic activity across sectors, or because firms with a relatively lower emissions profile than their sectoral peers are assessed as less creditworthy.

In Table 3, we show that similar results hold within sectors. We include to our empirical specification sectors fixed effects – defined as NACE sectors. In Panel A, we show that the coefficients for Scope 1 emissions remain of similar magnitude to those not controlling for industry fixed effects. Borrowers with Scope 1 carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 4% lower (higher) by lenders (Panel A: Column 3). The same result holds controlling for firms characteristics, although the magnitude decreases to 2.4% (Panel A: Column 4). Within sector results are also similar for Scope 3 emissions. In Panel B, we show that borrowers with Scope 3 absolute emissions one standard deviation higher (lower) than the mean are assigned a PD 4.8% lower (higher) by banks (Panel B: Column 3), and 3.2% lower when controlling for borrower-specific characteristics (Panel B: Column 4). Similarly to before, the coefficients become smaller when controlling for borrower-specific characteristics, but remain

14 We do not test this empirical specification with emission intensity as scaling emissions by revenues or assets (or any other proxy of size) correlates with our controls (e.g., assets, EBIT) and the business cycle

significant.

These results provide a nuanced perspective to our previous findings. Internal models estimates may be negatively correlated with carbon emissions controlling for borrower-specific characteristics of borrowers or not. But these relationship may also be present in relative terms within specific sectors. Not only firms with lower emissions are associated with higher capital requirements, but also firms that have a better emission profile compared to their peers (in the same sector) are assessed as riskier. Overall, our results seem to suggest that banks' internal models - and as a consequence Pillar I capital requirements - may not fully internalise transition risk. This suggests that the banking sector could be exposed to financial risks that are not captured by the current regulatory framework and that low-carbon firms may be receiving a less favourable treatment than high-carbon firms.

We then analyse differences between sectors following Giannetti et al. (2026) to further test the robustness of our results. We classify sectors that have the highest emission intensity – defined as sector's emissions divided by the Gross Value Added (GVA) of the sector above the median of all sectors – as high emitting. We also use a more granular classification to identify the sectors with the highest absolute emissions based on the NACE classification level 2[15]. We then create a dummy variable equal 1 if the debtor (borrower) is in one of the sectors and use our empirical specification replacing carbon emissions with the dummy variable. This approach not only allows us to study the relationship between sectors, but also provides an alternative measurement of transition risk than firms' carbon emissions – which have been often criticised for their reliability (Aswani et al., 2023).

In Table 4, we show that borrowers in both the highest emission intensity and absolute emissions are associated with lower Probability of Default. Borrowers in these sectors are associated with between 3.3% and 4.2% lower PD (Panel A: Columns 1 and 3). Consistently, results remain significant when controlling for borrower-specific characteristics,

15 Specifically we classify as high emissions: Mining of coal and lignite (B5), Extraction of crude petroleum and natural gas (B6), Manufacture of coke and refined petroleum product (C19), Manufacture of chemicals and chemical products (C20), Manufacture of other non-metallic mineral products (e.g. cement) (C23), Manufacture of basic metal (C24), Electricity gas steam and air conditioning supply (D35), Air transport (H51), Civil engineering (infrastructure construction) (F42), Land transport and transport via pipelines (H49), Water transport (H50).

though the coefficient on the emission dummy increases in magnitude (Column 4) while the emission intensity dummy remains broadly stable (Column 2).

We then turn to assess individual sectors focusing on some of the most polluting: Agriculture, Electricity, and Mining. We use a dummy variable equal 1 if the borrower is in the respective sector and 0 otherwise. In Table 4, we show that the coefficients for all these sectors are negative and statistically significant. Borrowers in the Agriculture sector are associated with 9.6% lower PD, borrowers in the Electricity sector are associated with a 9.3% lower PD, and borrowers in the Mining sector are associated with a 8.8% lower PD (significant at the 10% level). These results align with previous evidence showing that firms in some of the most emitting sectors may be associated with lower capital requirements. Similarly, in unreported results, we find that firms in the Oil & Gas sector[16], are associated with 8.4% lower PD than all firms in the energy sector.

Mitigating climate change will depend in large part on decarbonizing the energy sector and transitioning to clean electricity. The energy sector is responsible for around two-thirds of global emissions[17], making it central to transition risk: tightening climate policy, rising carbon prices, and shifting demand threaten to strand fossil-fuel assets while favoring low-carbon producers. The debate between continued fossil fuel use and the shift to renewables is, in effect, a debate about how this risk is distributed. Our previous results show that the electricity sector – in aggregate – is associated with lower capital requirements, a finding at odds with the sector's high transition risk exposure. However, the sector is highly heterogeneous. To better investigate this heterogeneity, we limit our sample to electricity companies[18] and test the relationship between PD estimates and borrowers' carbon emissions.

In Table 5, we show that firms in the electricity sectors display the same negative relationship that we find in our full sample. Borrowers with carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 2.3% lower (higher) by lenders for Scope 1 and 4.6% for Scope 3. This difference is mostly driven by low or zero-carbon electricity producers compared to utilities with various energy mix. However, the

16 We classify as Oil and Gas firms in the NACE sectors B5 (Mining of coal and lignite), B6 (Extraction of crude petroleum and natural gas), B9 (Mining support service activities), and C19 (Manufacture of coke and refined petroleum products)
17 Source: Our World In Data
18 Those classified in the NACE sector D: Electricity, gas, steam and air conditioning supply

coefficients in Table 5 become no longer significant when controlling for borrower-specific characteristics. This may indicate that - while overall low-carbon energy may be assessed as riskier by lenders - the explanation for this phenomenon may reside in the different financial structure of low-carbon vs high-carbon firms. For example, renewable energy may be intrinsically riskier than other forms of energy production (without considering transition risks) due to the higher leverage required by this activity.

This pattern is broadly consistent with how capital-requirement models are built: they lean on historical default experience and observable borrower financials rather than on forward-looking exposure to transition risk. High-emitting firms, particularly in energy, utilities, and heavy industry, typically carry sizeable tangible asset bases, well-established cash flows, and long-standing lending relationships, and these characteristics push standard credit-risk models toward lower estimated default risk even where they may coincide with greater exposure to transition risk down the line. To investigate this further, we examine whether differences in firms' underlying financial situation — rather than emissions per se — can account for these results. We select a sub-sample of Oil and Gas and Renewable energy firms and compare key profitability, solvency, and liquidity ratios across the two groups, allowing us to assess whether observed differentials in creditworthiness are driven by financial fundamentals. To make our analysis more representative, in this case, we rely on a global sample of firms from Bureau van Dijk's Orbis rather than on our Euro-area based data.

Table 6, shows that Oil and Gas firms have a better financial situation compared to Renewable energy firms. Oil and Gas firms have, on average, an Interest coverage ratio (IC) – defined as the ratio between Earnings Before Interest and Taxes (EBIT) and interest expenses – of 22 compared to 16 for renewable energy firms over the past 20 years and 29 compared to 18 in the past 5 years average. Oil and Gas firms have also, on average, a higher solvency ratio (SOLR) - defined as the ratio of total assets over total liabilities - and an average higher Current Ratio (CR) – defined as ratio of current assets over current liabilities – compared to Renewable energy firms. IC, SOLR, and CR are key solvency and liquidity measures assessed by financial risk models to estimate the probability of default of borrowers.[19] These are only some of the variables considered by

19 A related question is whether these firms have also better profit margins. We consider two profit

risk models for assessing the Probability of Default of borrowers, but our analysis shows that there could be some differences in the financial structure of high and low-carbon energy firms which may explain differentials in (estimated) creditworthiness.

We also explore the relationship between risk assessments and broader sustainability indicators, such as ESG ratings and the presence of a net-zero target. In Table 7 (Panel A), we find a negative association between lenders' estimates of borrowers' Probability of Default and ESG ratings. Since higher ESG ratings indicate stronger ESG performance and lower ESG-related risks, this result suggests that borrowers with better ESG profiles tend to receive more favourable risk assessments. However, unlike the results for carbon emissions, the relationship is not robust across specifications. The coefficient is negative and statistically significant in the baseline specification, but becomes statistically insignificant once borrower characteristics are included. The estimated effects range from -1.2% to -1.8% across specifications. Overall, the evidence points to a weaker and less robust relationship between ESG ratings and lenders' internal risk assessments than the relationship documented for borrowers' carbon emissions.

We then examine whether borrowers with publicly disclosed net-zero targets are associated with lower risk assessments. Net-zero commitments may contribute to future emissions reductions and could therefore be perceived by lenders as reducing firms' exposure to transition-related risks. In Table 7 (Panel B), we report regressions of lenders' estimates of borrowers' Probability of Default (PD) on a dummy variable equal to one if the borrower has a publicly disclosed net-zero target, using information from Refinitiv. We find that borrowers with a net-zero target are associated with substantially lower estimated probabilities of default. In the baseline specifications, the coefficients imply PDs that are around 14% lower for firms with a target (Panel B: Columns 1 and 3). However, the magnitude of the relationship declines markedly once borrower characteristics are included, falling to around 2–3%, and the statistical significance becomes only marginal (Panel B: Columns 2 and 4). These results suggest that lenders associate net-zero commitments with lower perceived risk, although much of this relationship appears to reflect underlying differences in borrower characteristics rather than an independent effect of

margin measures: the EBIT margin – defined as EBIT over total revenues – and the Gross Margin – defined as gross profits over total revenues. Differently from previous results Renewable energy companies have generally better profitability margins.

the target itself.

We now discuss some of the implications of these differentials. We start by assessing whether carbon emissions are associated with higher interest rates charged by banks to firms. In Table 8, we show a negative and statistically significant relationship between the spread over the risk-free rate charged to borrowers by lenders and borrowers' carbon emissions. Borrowers with Scope 1 emissions one standard deviation higher (lower) than the mean are associated with 8.3% (Column 1) to 8.8% (Column 3) lower (higher) interest rates by banks, on average. For Scope 3 emissions, borrowers one standard deviation higher are associated with 10.4% (Column 1) to 10.7% (Column 3) lower interest rates (Panel B). When controlling for borrowers' characteristics, the coefficients decrease in magnitude but remain negative and generally statistically significant. For Scope 1 emissions, the estimated effects fall to around 5.6–5.9% (Panel A: Columns 2 and 4), while for Scope 3 emissions they remain economically sizeable at around 8.5–8.8% (Panel B: Columns 2 and 4), consistent with our previous findings on the relationship between emissions and PD. Not surprisingly, differences in borrowers' estimated risk appear to feed directly through into loan pricing.

Although these results may arise from various factors, including differences in banks' willingness to lend across sectors, they are likely to be driven, at least in part, by differences in risk assessments. First, as shown in Figure 1, Panel A, there is a strong positive relationship between borrowers' estimated Probability of Default and the interest rates charged by banks. This is also aligned with anecdotal evidence and regulatory guidance on incorporating risk assessments in loan origination and pricing. Secondly, there is supporting evidence from the literature on the macro-economic effects of capital requirements (Gropp et al., 2019; Benetton et al., 2021). Finally, it seems rational that – in a profit maximizing framework – banks seek to select financing opportunities based on their Risk Adjusted Return on capital. Hence, it is likely that higher risk estimates for low emitting firms result in higher cost of funding for those borrowers.

Taken together, these results consistently suggest that banks' internal models may not price transition risk: low-carbon borrowers face higher probability-of-default estimates, higher capital requirements, and higher loan spreads than their high-carbon peers, both across and within sectors, even after accounting for standard financial fundamentals. This pattern stands in contrast to the weaker and less robust relationship we document for ESG ratings and the stronger baseline relationship observed for net-zero commitments.

These findings carry direct implications for prudential regulation. If banks' internal models do not price transition risk, Pillar I capital requirements calibrated on these models may understate banks' true risk exposure to high-carbon borrowers, pointing to a possible role for Pillar II measures such as climate stress testing or supervisory add-ons. At the same time, if low-carbon borrowers face funding costs that do not reflect their lower transition risk, this could raise their cost of capital and slow investment in decarbonization, partially offsetting the aims of climate policy elsewhere in the economy.

5 Conclusion

This paper shows that banks' internal models used for prudential regulation—specifically under Pillar I capital requirements—may not price transition risk. We find a negative and statistically significant relationship between lenders' risk estimates and borrowers' carbon emissions, both within and across sectors, including within the energy and power generation sector, where transition risk is most salient. Our results are robust across alternative specifications and measures of carbon emissions. These findings have implications for how banks determine and allocate capital requirements, which may not fully incorporate transition risk, and how they price loans, increasing the cost of funding for low-carbon activities and potentially constraining the availability of finance to them. We suggest that this pattern may reflect the Internal Ratings-Based (IRB) approach reliance on historical data, which may inadequately capture long-term forward-looking risks, as well as structural differences in the financial profiles of low- and high-carbon borrowers, particularly in the energy sector. Overall, our results highlight the need for further research on the design of capital requirement frameworks that better align with emerging central bank and supervisory efforts to incorporate climate-related financial risks.

References

Admati, A. R. and Hellwig, M. F. (2013). *The Bankers' New Clothes: What's Wrong with Banking and What to Do about It*. Princeton University Press.

Allen, F., Carletti, E., and Marquez, R. (2011). Credit market competition and capital regulation. *The Review of Financial Studies*, 24(4):983–1018.

Altavilla, C., Boucinha, M., Pagano, M., and Polo, A. (2024). Climate risk, bank lending and monetary policy. *ECB Working Paper*.

Aswani, J., Raghunandan, A., and Rajgopal, S. (2023). Are carbon emissions associated with stock returns? *Review of Finance*, 28(1):75–106.

Baker, M. and Wurgler, J. (2015). Do strict capital requirements raise the cost of capital? bank regulation, capital structure, and the low-risk anomaly. *American Economic Review*, 105(5):315–320.

Bednarek, P., Briukhova, O., Ongena, S., and von Westernhagen, N. (2025). Effects of bank capital requirements on lending by banks and non-bank financial institutions. *Journal of Financial Intermediation*, 63.

Behn, M., Haselmann, R., and Vig, V. (2022). The limits of model-based regulation. *The Journal of Finance*, 77(3):1635–1684.

Behn, M., Haselmann, R., and Wachtel, P. (2016). Procyclical capital regulation and lending. *The Journal of Finance*, 71(2):919–956.

Benetton, M., Eckley, P., Garbarino, N., Kirwin, L., and Latsi, G. (2021). Capital requirements and mortgage pricing: Evidence from basel ii. *Journal of Financial Intermediation*, 48.

Bernanke (2023). Nobel lecture: Banking, credit, and economic fluctuations. *American Economic Review*, 113(5).

Bernanke, B. S. and Gertler, M. (1990). Financial fragility and economic performance. *The Quarterly Journal of Economics*, 105(1):87–114.

Beyene, W., De Greiff, K., Delis, M. D., and Ongena, S. (2021). Too-big-to-strand? bond versus bank financing in the transition to a low-carbon economy. CEPR Discussion Paper DP16692, CEPR.

Blum, J. and Hellwig, M. (1995). The macroeconomic implications of capital adequacy requirements for banks. *European Economic Review*, 39(3-4):739–749.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, 78(6):3677–3754.

Campiglio, E., Dafermos, Y., Monnin, P., et al. (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change*, 8:462–468.

Carbone, S., Giuzio, M., Kapadia, S., Krämer, J. S., Nyholm, K., and Vozian, K. (2025). The low-carbon transition, climate commitments and firm credit risk. *Working Paper*.

Crouhy, M. and Galai, D. (1986). An economic assessment of capital requirements in the banking industry. *Journal of Banking & Finance*, 10(2):231–241.

de Bandt, O., Kuntz, L.-C., Pankratz, N., Pegoraro, F., Solheim, H., Sutton, G., Takeyama, A., and Xia, F. D. (2025). The effects of climate change-related risks on banks: A literature review. *Journal of Economic Surveys*, 39(4):1553–1594.

Delis, M. D., Greiff, K. d., Iosifidi, M., and Ongena, S. (2024). Being stranded with fossil fuel reserves? climate policy risk and the pricing of bank loans. *Financial markets, institutions & instruments*, 33(3):239–265.

Dewatripont, M. and Tirole, J. (1994). *The Prudential Regulation of Banks*. MIT Press.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

Diamond, D. W. and Rajan, R. G. (2001). Banks and liquidity. *American Economic Review*, 91(2):422–425.

Edmans, A. and Kacperczyk, M. (2022). Sustainable Finance. *Review of Finance*, 26(6):1309–1313.

Ehlers, T., Packer, F., and de Greiff, K. (2022). The pricing of carbon risk in syndicated loans: Which risks are priced and why? *Journal of Banking and Finance*, 136:106180.

European Banking Authority (2023). Report on the role of environmental and social risks in the prudential framework. Technical Report EBA/REP/2023/34, European Banking Authority.

European Central Bank (2020). Guide on climate-related and environmental risks: Supervisory expectations relating to risk management and disclosure. Technical report, European Central Bank, Banking Supervision.

Fraisse, H., Lé, M., and Thesmar, D. (2020). The real effects of bank capital requirements. *Management Science*, 66(1):5–23.

Gasparini, M., Ives, M. C., Carr, B., Fry, S., and Beinhocker, E. (2024). Model-based financial regulations impair the transition to net-zero carbon emissions. *Nature Climate Change*, 14.

Gasparini, M. and Tufano, P. (2023). The evolving academic field of climate finance. *Working Paper*, (23-057).

Giannetti, M., Jasova, M., Loumioti, M., and Mendicino, C. (2026). "glossy green" banks: The disconnect between environmental disclosures and lending activities. *Management Science*, 0(0).

Giglio, S., Kelly, B., and Stroebel, J. (2021). Climate Finance. *Annual Review of Financial Economics*, 13:15–36.

Goodhart, C. A., Kashyap, A. K., Tsomocos, D. P., and Vardoulakis, A. P. (2012). Financial regulation in general equilibrium. *Working Paper*.

Gropp, R., Mosk, T., Ongena, S., and Wix, C. (2019). Banks' response to higher capital requirements: Evidence from a quasi-natural experiment. *The Review of Financial Studies*, 32(1):266–299.

Hellmann, T. F., Murdock, K. C., and Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *The American Economic Review*, 90(1):147–165.

Holmström, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, 112(3):663–691.

Ivanov, I. T., Kruttli, M. S., and Watugala, S. W. (2024). Banking on carbon: Corporate lending and cap-and-trade policy. *The Review of Financial Studies*, 37(5):1640–1684.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers, and credit supply: Evidence from the spanish dynamic provisioning experiments. *Journal of Political Economy*, 125(6):2126–2177.

Mehran, H. and Thakor, A. (2011). Bank capital and value in the cross-section. *The Review of Financial Studies*, 24(4):1019–1067.

Molyneux, P., Reghezza, A., Thornton, J., and Xie, R. (2020). Did negative interest rates improve bank lending? *Journal of Financial Services Research*, 57(1):51–68.

Myerson, R. B. (2014). Rethinking the principles of bank regulation: A review of admati and hellwig's the bankers' new clothes. *Journal of Economic Literature*, 52(1):197–210.

Oehmke, M. and Opp, M. M. (2025). Green capital requirements: Prudential regulation, credit allocation, and climate policy. *Journal of Finance*. Forthcoming.

Papoutsi, M., Piazzesi, M., and Schneider, M. (2021). How unconventional is green monetary policy? *Working paper*.

Plosser, M. C. and Santos, J. A. C. (2018). Banks' incentives and inconsistent risk models. *The Review of Financial Studies*, 31(6):2080–2112.

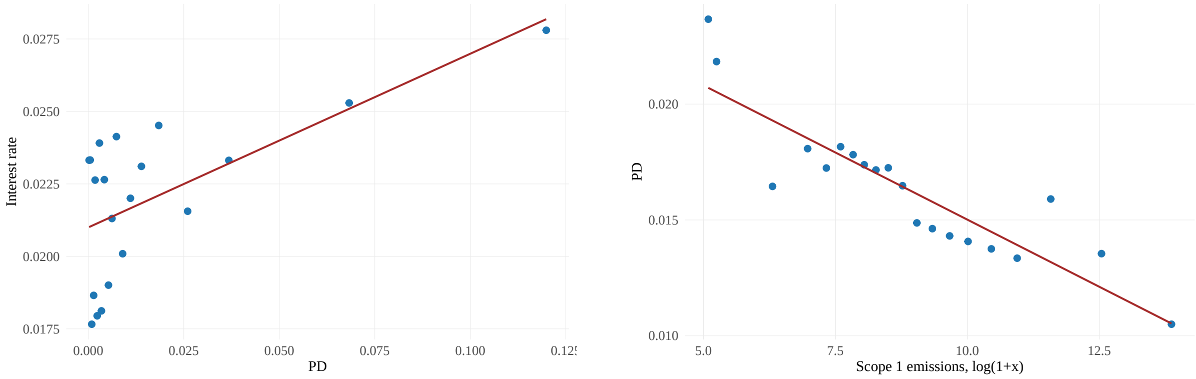
Rochet, J.-C. (1992). Capital requirements and the behaviour of commercial banks. *European Economic Review*, 36(5):1137–1170.

Seltzer, L. H., Starks, L., and Zhu, Q. (2022). Climate regulatory risk and corporate bonds. *Working Paper*.

Thakor, A. V. (2014). Bank capital and financial stability: An economic trade-off or a faustian bargain? *Annual Review of Financial Economics*, 6:185–223.

6 Tables and Figures

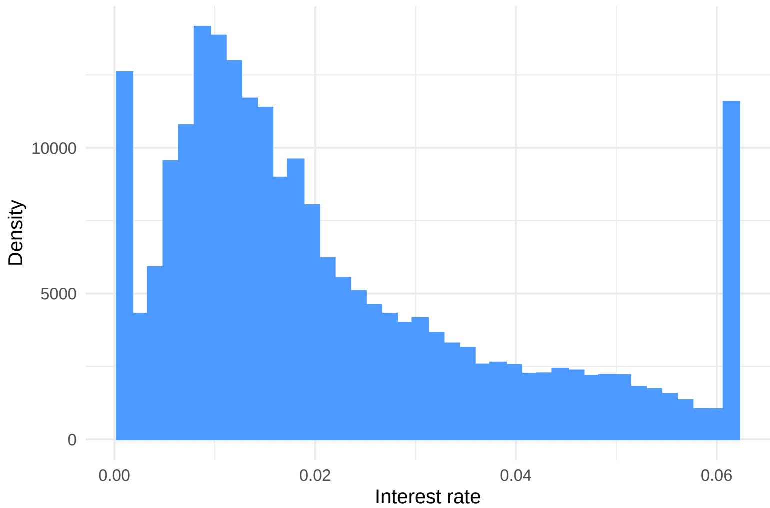
Figure 1: Credit risk, loan pricing, and emissions



(a) PD and interest rate **(b)** PD and Scope 1 emissions

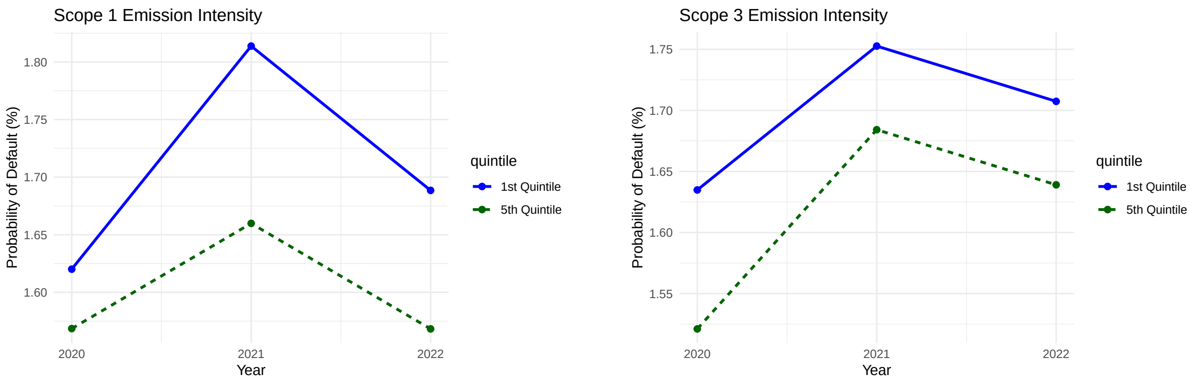
Notes: Panel A presents a binned scatterplot of the relationship between borrower probability of default and the interest rate charged on loans. Panel B presents the relationship between borrower probability of default and Scope 1 carbon emissions. Data are winsorized at the 5th and 95th percentiles.

Figure 2: Distribution of interest rates



Notes: The figure displays the distribution of interest rates in the sample. Data are winsorized at the 5th and 95th percentiles.

Figure 3: Probability of default and emission intensity



(a) Scope 1 emission intensity **(b)** Scope 3 emission intensity

Notes: The figure compares the average probability of default of borrowers in the first and fifth quintiles of the emission-intensity distribution. Quintile 1 corresponds to the lowest-emission-intensity borrowers, while Quintile 5 corresponds to the highest-emission-intensity borrowers. Panel A uses Scope 1 emission intensity and Panel B uses Scope 3 emission intensity.

Panel A: Number of Debtors by Country

	Country debtor				
Country creditor	Germany	Spain	France	Italy	Total
Germany	3,207	100	275	109	3,691
Spain	112	1,132	112	75	1,431
France	309	138	3,134	182	3,763
Italy	89	44	123	1,405	1,661

Panel B: Probability of Default by Fiscal Year

Fiscal Year	Mean	Standard dev	Minimum	Maximum	N
2019	3.91%	15.96%	0%	100%	39,572
2020	4.01%	15.84%	0%	100%	40,622
2021	4.48%	16.47%	0%	100%	41,832
2022	4.52%	16.58%	0%	100%	41,771
2023	4.84%	17.89%	0%	100%	42,210
2024	5.23%	19.21%	0%	100%	41,701
Total	4.51%	17.03%	0%	100%	247,708

Panel C: Probability of Default by Country

Country	Mean	Standard dev	Minimum	Maximum	N
Germany	3.69%	16.01%	0%	100%	94,339
Spain	5.70%	17.63%	0%	100%	31,673
France	4.76%	17.08%	0%	100%	70,649
Italy	4.69%	17.71%	0%	100%	51,047
Total	4.51%	17.03%	0%	100%	247,708

Table 1: Descriptive statistics. The table reports descriptive statistics for the main variables of interest in our sample. Data span January 2019 to December 2024. **Panel A** reports the number of creditor–debtor (lender–borrower) relationships in the sample, by creditor (lender) country and debtor (borrower) country, for the four main countries in our dataset. **Panel B** reports the mean, standard deviation, minimum, maximum, and number of observations for lenders' estimates of borrowers' Probability of Default (PD), by fiscal year. **Panel C** reports the mean, standard deviation, minimum, maximum, and number of observations for lenders' estimates of borrowers' Probability of Default (PD), by debtor (borrower) country.

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
CFOP	0.001	0.000	-0.001	-0.001
	(0.006)	(0.006)	(0.005)	(0.005)
ETMA	-0.033***	-0.033***	-0.026***	-0.026***
	(0.006)	(0.006)	(0.006)	(0.006)
TOAS	-0.057***	-0.055***	-0.053***	-0.051***
	(0.006)	(0.006)	(0.007)	(0.007)
ROA	-0.023***	-0.024***	-0.024***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)
SOLR	-0.033***	-0.032***	-0.037***	-0.036***
	(0.006)	(0.007)	(0.006)	(0.006)
AGE	-0.022***	-0.022***	-0.020***	-0.019***
	(0.005)	(0.005)	(0.004)	(0.004)
Spain	0.115***	0.117***	0.066	0.072
	(0.031)	(0.031)	(0.056)	(0.054)
France	0.114***	0.115***	0.010	0.012
	(0.020)	(0.020)	(0.031)	(0.031)
Time FE	N	Y	N	Y
Creditor FE	N	N	Y	Y
Observations	21,037	21,037	21,020	21,020
R-Squared	0.104	0.109	0.193	0.197

Table 2: Probability of default and firm financial characteristics. The table reports the results of a regression of lenders' estimates of borrower-level Probability of Default (PD) on standard borrower-level financial characteristics: Cash Flow to Revenue (CFOP), EBIT Margin (ETMA), Total Assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), Age of borrower (AGE), and debtor (borrower) country. Data are winsorized at the 5th and 95th percentiles. Sample period: January 2019 to December 2024. Columns (1) and (2) include time fixed effects; Columns (3) and (4) include creditor fixed effects; Columns (2) and (4) include time fixed effects. Standard errors, clustered at the creditor–debtor (bank–firm) level, are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Scope 1 Emissions

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Emissions (log)	-0.036***	-0.020***	-0.040***	-0.024***
	(0.004)	(0.005)	(0.005)	(0.006)
CFOP		-0.003		-0.007
		(0.005)		(0.005)
ETMA		-0.028***		-0.016**
		(0.006)		(0.006)
TOAS		-0.042***		-0.044***
		(0.007)		(0.007)
ROA		-0.022***		-0.022***
		(0.004)		(0.004)
SOLR		-0.037***		-0.043***
		(0.006)		(0.005)
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	40,903	20,960	40,901	20,957
R-Squared	0.119	0.195	0.138	0.225

Panel B: Scope 3 Emissions

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 3 Emissions (log)	-0.045***	-0.026***	-0.048***	-0.032***
	(0.005)	(0.005)	(0.005)	(0.005)
CFOP		-0.003		-0.007
		(0.005)		(0.005)
ETMA		-0.030***		-0.018**
		(0.006)		(0.006)
TOAS		-0.037***		-0.038***
		(0.007)		(0.007)
ROA		-0.022***		-0.021***
		(0.004)		(0.004)
SOLR		-0.037***		-0.043***
		(0.005)		(0.005)
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	40,903	20,960	40,901	20,957
R-Squared	0.123	0.196	0.141	0.226

Table 3: Probability of default and carbon emissions. The table reports the results of a regression of lenders' estimates of borrower-level Probability of Default (PD) on debtors' (borrowers') log Scope 1 (**Panel A**) and log Scope 3 (**Panel B**) carbon emissions. Control variables, where included, are Cash Flow to Revenue (CFOP), EBIT Margin (ETMA), Total Assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and Age of borrower (not reported), and debtor (borrower) country (not reported). Data are winsorized at the 5th and 95th percentiles. Sample period: January 2019 to December 2024. All columns include creditor (lender) fixed effects. Standard errors, clustered at the creditor–debtor (bank–firm) level, are reported in parentheses. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Panel A: Emissions

	(1)	(2)	(3)	(4)
Emission dummy	-0.033***	-0.030*		
	(0.009)	(0.013)		
Emission intensity dummy			-0.042**	-0.064***
			(0.013)	(0.017)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	52,529	21,020	49,920	19,436
R-Squared	0.114	0.198	0.108	0.192

Panel B: Sectors

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Agriculture	-0.096***			
	(0.020)			
Electricity		-0.093***		
		(0.012)		
Mining			-0.088*	
			(0.042)	
Civil engineering				-0.112**
				(0.040)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	21,020	21,020	21,020	21,020
R-Squared	0.197	0.199	0.197	0.199

Table 4: Probability of default and emitting sectors. The table reports the results of a regression of lenders' estimates of borrower-level Probability of Default (PD) on debtor (borrower) sector classifications. **Panel A** reports results using two alternative sector-level emissions classifications. The *Emission dummy* (Columns 1–2) equals one if the debtor (borrower) operates in one of the following high absolute-emissions sectors (NACE Rev. 2, 2-digit level): Mining of coal and lignite (B5); Extraction of crude petroleum and natural gas (B6); Manufacture of coke and refined petroleum products (C19); Manufacture of chemicals and chemical products (C20); Manufacture of other non-metallic mineral products, e.g., cement (C23); Manufacture of basic metals (C24); Electricity, gas, steam and air conditioning supply (D35); Air transport (H51); Civil engineering / infrastructure construction (F42); Land transport and transport via pipelines (H49); and Water transport (H50). The *Emission intensity dummy* (Columns 3–4) equals one if the debtor (borrower) operates in one of the following high emission-intensity sectors: Electricity, gas, steam and air conditioning supply; Agriculture, forestry and fishing; Water supply, sewerage, waste management and remediation activities; and Mining and quarrying. **Panel B** reports results for individual sector dummies, estimated in separate regressions (Columns 1–4), for four of the highest-emitting sectors: Agriculture, Electricity, Mining, and Civil engineering. Control variables, where included, are Cash Flow to Revenue (CFOP), EBIT Margin (ETMA), Total Assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), Age of borrower (AGE), and debtor (borrower) country (all not reported). Data are winsorized at the 5th and 95th percentiles. Sample period: January 2019 to December 2024. All columns include time and creditor (lender) fixed effects. Standard errors, clustered at the creditor–debtor (bank–firm) level, are reported in parentheses. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Emissions (log)	-0.023*	0.010		
	(0.011)	(0.012)		
Scope 3 Emissions (log)			-0.046**	0.010
			(0.017)	(0.024)
CFOP		0.000		-0.001
		(0.015)		(0.015)
ETMA		-0.038+		-0.035+
		(0.020)		(0.020)
TOAS		-0.002		-0.005
		(0.035)		(0.039)
ROA		-0.003		-0.004
		(0.015)		(0.015)
SOLR		-0.016		-0.017
		(0.024)		(0.024)
AGE		-0.018***		-0.019***
		(0.004)		(0.004)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	1,230	613	1,230	613
R-Squared	0.337	0.395	0.347	0.393

Table 5: Probability of default and carbon emissions: Electricity sector. The table reports the results of a regression of lenders' estimates of borrower-level Probability of Default (PD) on debtor (borrower) log Scope 1 (Columns 1–2) and log Scope 3 (Columns 3–4) carbon emissions, restricted to the sample of electricity companies (NACE Rev. 2 sector D: Electricity, gas, steam and air conditioning supply). Control variables, where included, are Cash Flow to Revenue (CFOP), EBIT Margin (ETMA), Total Assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and Age of borrower (AGE). Data are winsorized at the 5th and 95th percentiles. Sample period: January 2019 to December 2024. All columns include time and creditor (lender) fixed effects. Standard errors, clustered at the creditor–debtor (bank–firm) level, are reported in parentheses. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1

	Interest Coverage		Current Ratio		Solvency Ratio		EBIT Margin		Gross Profit Margin	
	HC	LC	HC	LC	HC	LC	HC	LC	HC	LC
2004	22	15.94	3.71	2.11	56.96	35.46	16.72	13.41	54.74	48.95
2005	26.15	16.18	4.72	2.29	59.74	37.42	19.95	13.92	55.6	48.93
2006	21.87	28.51	4.34	2.02	57.11	35.48	14.99	14.11	48.95	37.74
2007	13.53	16.78	4.15	1.94	55.97	35.74	12.41	15.16	46.99	36.5
2008	13.45	12.39	3.99	2.04	55.5	36.26	12.4	11.56	44.39	32.32
2009	10.25	10.1	3.89	2.52	55.67	36.34	4.93	14.83	42.11	38.16
2010	17.28	21.57	4.24	3.04	55.78	36.71	9.43	16.49	42.62	41.57
2011	22.92	11.58	3.5	2.4	53.96	34.24	11.89	15.99	41.46	41.39
2012	23.2	13.28	3.05	2.73	52.24	33.98	11.7	18.09	41.14	44.66
2013	25.32	13.11	3.11	2.83	47.69	33.77	12.57	18.35	36.44	54.62
2014	25.43	12.2	3.43	3.12	46.25	34.94	10.63	19.51	35.04	53.76
2015	14.09	14.52	3.27	3.28	45.28	35.36	3.99	20.43	34.67	57
2016	16.03	13.8	3.59	3.26	45.87	34.86	4.11	20.18	34.36	58.01
2017	22.23	14.33	3.55	3.16	45.99	34.31	7.41	23.24	35.11	59.07
2018	24.19	15.36	3.51	3.25	46.02	33.52	11.85	24.01	38.89	59.69
2019	23.1	16.55	3.58	3.42	45.77	34.27	10.34	24.39	38	60.15
2020	17.1	15.69	3.72	3.36	45.56	34.3	3.78	22.71	33.92	60.67
2021	29.83	19.89	3.76	3.17	46.35	33.4	13.42	26.72	38.44	61.32
2022	40.46	24.6	3.81	3.06	46.87	33.46	17.01	29.83	40.07	60.9
2023	35.45	16.11	3.48	2.72	54.18	32.09	14.76	27.89	43.22	63.74
20Y Avg.	22.19	16.12	3.72	2.79	50.94	34.8	11.21	19.54	41.31	50.96
10Y Avg.	24.79	16.31	3.57	3.18	46.81	34.05	9.73	23.89	37.17	59.43
5Y Avg.	29.19	18.57	3.67	3.15	47.75	33.5	11.86	26.31	38.73	61.36

Table 6: Profitability, solvency, and liquidity metrics: Oil and Gas versus Renewable energy firms. The table reports yearly averages of key profitability, solvency, and liquidity ratios for the universe of large Oil and Gas (HC, high-carbon) and Renewable energy (LC, low-carbon) firms in Bureau van Dijk's Orbis, 2004–2023. Interest Coverage is defined as Earnings Before Interest and Taxes (EBIT) divided by interest expenses; Current Ratio is current assets divided by current liabilities; Solvency Ratio is total assets divided by total liabilities; EBIT Margin is EBIT divided by total revenues; and Gross Profit Margin is gross profit divided by total revenues. Renewable energy firms (LC) are classified using NAICS codes 221114, 221115, 221116, 221117, and 221118; Oil and Gas firms (HC) are classified using NAICS codes 211120, 211130, 213111, 213112, 237120, 486110, 486210, and 486910. The bottom three rows report unweighted averages over the trailing 20-year, 10-year, and 5-year periods, respectively.

Panel A: ESG rating

	PD	PD	PD	PD
ESG Rating	-0.121**	-0.026	-0.080+	-0.018
	(0.043)	(0.055)	(0.041)	(0.061)
CFOP		-0.029**		-0.028**
		(0.010)		(0.010)
ETMA		0.021+		0.033*
		(0.012)		(0.014)
TOAS		-0.029***		-0.027**
		(0.007)		(0.009)
ROA		-0.039**		-0.037*
		(0.014)		(0.017)
SOLR		-0.013		-0.029+
		(0.012)		(0.016)
AGE		-0.002		0.000
		(0.010)		(0.011)
Time FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	3,030	1,426	3,028	1,422
R-Squared	0.016	0.120	0.083	0.183

Panel B: net-zero targets

	PD	PD	PD	PD
Target	-0.144***	-0.024+	-0.137***	-0.028+
	(0.013)	(0.014)	(0.014)	(0.015)
CFOP		0.001		-0.005
		(0.006)		(0.005)
ETMA		-0.033***		-0.016**
		(0.006)		(0.006)
TOAS		-0.053***		-0.056***
		(0.007)		(0.007)
ROA		-0.023***		-0.023***
		(0.004)		(0.004)
SOLR		-0.033***		-0.039***
		(0.006)		(0.006)
AGE		-0.022***		-0.021***
		(0.005)		(0.004)
Time FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	52,542	21,037	52,541	21,034
R-Squared	0.008	0.104	0.042	0.139

Table 7: **Probability of default and ESG factors.** The table reports the results of a regression of lenders' estimates of borrower-level Probability of Default (PD) on **Panel A** MSCI environmental, social, and governance (ESG) ratings, and **Panel B** a dummy variable equal to one if the borrower has a publicly disclosed net-zero target (source: Refinitiv). Control variables, where included, are Cash Flow to Revenue (CFOP), EBIT Margin (ETMA), Total Assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and Age of borrower (AGE). Columns (3) and (4) additionally include NACE sector fixed effects. Data are winsorized at the 5th and 95th percentiles. Sample period: January 2019 to December 2024. Standard errors, clustered at the creditor–debtor (bank–firm) level, are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Panel A: Scope 1 Emissions

	(1)	(2)	(3)	(4)
	Spread	Spread	Spread	Spread
Scope 1 Emissions	-0.083***	-0.059*	-0.088***	-0.056+
	(0.015)	(0.029)	(0.016)	(0.029)
CFOP		0.040		0.029
		(0.033)		(0.030)
ETMA		0.004		-0.001
		(0.029)		(0.031)
TOAS		-0.034		-0.036
		(0.028)		(0.028)
ROA		-0.059*		-0.057*
		(0.026)		(0.023)
SOLR		0.030		0.031
		(0.022)		(0.021)
AGE		-0.067**		-0.072***
		(0.021)		(0.021)
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	19,841	7,160	19,838	7,157
R-Squared	0.290	0.339	0.299	0.351

Panel B: Scope 3 Emissions

	(1)	(2)	(3)	(4)
	Spread	Spread	Spread	Spread
Scope 3 Emissions	-0.104***	-0.088**	-0.107***	-0.085*
	(0.016)	(0.034)	(0.018)	(0.037)
CFOP		0.039		0.031
		(0.033)		(0.030)
ETMA		-0.007		-0.007
		(0.030)		(0.030)
TOAS		-0.013		-0.016
		(0.026)		(0.028)
ROA		-0.058*		-0.056*
		(0.026)		(0.023)
SOLR		0.034		0.033
		(0.021)		(0.021)
AGE		-0.065**		-0.070**
		(0.022)		(0.022)
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	19,841	7,160	19,838	7,157
R-Squared	0.291	0.341	0.300	0.352

Table 8: **Interest rates and carbon emissions.** The table reports the results of a regression of lenders' interest rate spread above the risk-free rate charged to borrowers on debtor (borrower) log Scope 1 (**Panel A**) and log Scope 3 (**Panel B**) carbon emissions. Control variables, where included, are Cash Flow to Revenue (CFOP), EBIT Margin (ETMA), Total Assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and Age of borrower (AGE). All columns include creditor (lender) fixed effects. Columns (3) and (4) additionally include NACE sector fixed effects. Data are winsorized at the 5th and 95th percentiles. Sample period: January 2019 to December 2024. Standard errors, clustered at the creditor–debtor (bank–firm) level, are reported in parentheses. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$, + $p< 0.1$.

A Data

This appendix documents the construction of the analysis sample and key data-processing choices. It also provides additional descriptive statistics and robustness diagnostics to support the empirical specifications in the main text.

The starting point of the analysis is the ECB AnaCredit credit register, which provides lender–borrower relationships and bank-assigned probabilities of default (PDs) for corporate exposures. We merge AnaCredit with firm-level financial information from Bureau van Dijk Orbis and carbon emissions from S&P Trucost. Matching is performed in two stages: (i) mapping AnaCredit debtor identifiers to Orbis BvD identifiers via ECB matching procedures and country-specific identifiers, and (ii) mapping Orbis BvD identifiers to Trucost identifiers using Capital IQ fuzzy matching based on company names and ISIN codes, with manual verification for non-exact matches. The matched sample is therefore limited to the subset of firms for which emissions data are available.

The unit of observation is the lender–borrower–year. Borrower characteristics such as emissions and balance-sheet variables are observed at the borrower–year level, while PDs are reported separately by each lender for the same borrower–year. As a result, the same borrower–year appears multiple times across different lenders. The number of lenders per borrower–year is highly heterogeneous and right-skewed; we document its distribution in Table A.1 and Figure A.1.

mean	p25	median	p75	p90	p99	max
5.582278	2	3	6	11	44	349

Table A.1: Distribution of the number of lenders per borrower–year

Because the number of lender relationships per borrower–year is skewed, a small number of highly connected borrowers can appear many times in the lender–borrower–year panel. To avoid these “hub” observations disproportionately affecting estimation and inference, we cap the number of concurrent lender relationships per borrower–year in the baseline sample. In the main specification, we restrict the sample to borrower–years with at most five lenders. We report robustness to alternative thresholds (e.g., 10 and no cap) and to reweighting schemes that assign equal total weight to each borrower–year in the

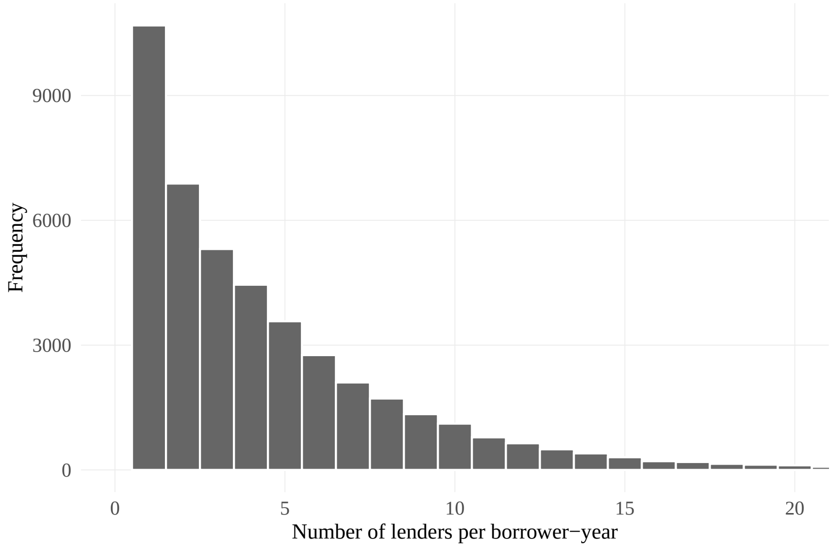


Figure A.1: Distribution of the number of lenders per borrower–year

Robustness Sub Section B.

We restrict the sample to performing exposures and exclude mechanically extreme PD values to ensure comparability across lenders and avoid observations outside the standard IRB modelling regime. Specifically, we apply the following filters:

- **Performing exposures:** we restrict to observations with days-past-due equal to zero ($dpd = 0$).
- **PD support:** we retain observations with $0.0006 < PD < 0.04$.

These restrictions focus the analysis on lender-assigned PDs in the range relevant for standard risk-weight calculations and exclude observations where PDs are driven by delinquency or mechanical floors (e.g., PD floor). Table A.2 reports the evolution of sample size across filters.

Step	Observations	Remaining Share
Raw sample	279272	1.000
After country filter	247708	0.887
After performing exposures ($dpd = 0$)	231051	0.827
After PD bounds ($0.0006 < PD < 0.04$)	83913	0.300
After trimming (max 5 lenders per borrower-year)	52542	0.188

Table A.2: Sample size across filtering steps

Several variables in the dataset exhibit strong right-skewness and heavy tails, notably emissions (especially Scope 3), credit spreads, and accounting ratios. To limit the influence of extreme observations while retaining the full sample, we winsorise continuous variables. Unless stated otherwise, winsorisation is implemented at the 5th and 95th percentiles. For selected variables with particularly heavy tails (e.g., loan-to-value), we apply alternative bounds (e.g., 10th–90th percentiles).

For ease of interpretation and numerical stability in estimation, we standardise continuous variables after winsorisation. In particular, we compute $x_s = (x - \bar{x})/\sigma_x$ using the full (winsorised) sample prior to the application of subsequent subsample restrictions. As a consequence, standardised variables do not necessarily have mean zero within the final analysis sample; this reflects the non-random nature of filtering and trimming. Table A.3 reports summary statistics for key variables in both winsorised and standardised form.

Variable	Mean	SD	P25	Median	P75
PD	0	1	−0.523	−0.385	−0.023
Scope 1 intensity	0	1	−0.389	−0.367	−0.229
Scope 2 intensity	0	1	−0.422	−0.387	−0.197
Scope 3 intensity	0	1	−0.468	−0.423	−0.131
CFOP	0	1	−0.592	−0.376	0.172
ETMA	0	1	−0.360	−0.150	0.274
ROA	0	1	−0.560	−0.101	0.530
Solvency ratio	0	1	−0.754	−0.042	0.691

Table A.3: Summary statistics for regression variables (standardised)

Summary statistics confirm that variables are standardised to have mean zero and unit variance. Despite winsorisation, the distributions remain asymmetric, particularly for emission measures and profitability indicators, reflecting substantial heterogeneity across firms.

We measure borrower carbon exposure using firm-level greenhouse gas emissions from Trucost. Emissions are observed at the borrower–year level and include Scope 1 and Scope 3 emissions. Given the strong right-skewness of emissions and the presence of very small values, the baseline specification uses log emissions. The main text focuses on log Scope 1 or log Scope 3 emissions.

We use the NACE classification to construct sector indicators for high-emissions and high-emissions-intensity sectors, as well as dummies for selected sectors of interest (e.g., agriculture, electricity, mining, and transport). Sector indicators are constructed based on NACE codes; missing NACE values are retained as unknown and excluded from sector-split descriptives unless explicitly stated. Table A.4 reports the distribution of observations across sector categories.

Sector	Observations	Firms
Transport	1888	226
Electricity	1481	218
Warehousing	1194	143
Fabricated metals	1170	132
Basic metals	1093	144
Chemicals	1040	138
Rubber and plastics	886	102
Civil engineering	739	73
Non-metallic minerals	725	87
Land transport	505	60
Renewables	254	35
Agriculture	207	31
Oil and gas	174	25
Fossil chain	169	23
Mining	39	13
Wind and solar	5	1

Table A.4: Distribution of observations across selected sector and energy dummies

Table A.5 compares key variables across high- and low-emission sectors.

Section	NACE	Description	Emission category	Observations	Firms
F	42	Civil engineering	High	739	73
H	49	Land transport and transport via pipelines	High	505	60
H	50	Water transport	High	139	18
E	39	Remediation activities and other waste management services	Medium	15	3
A	2	Forestry and logging	Medium	13	2
H	52	Warehousing and support activities for transportation	Medium-High	1194	143
C	25	Manufacture of fabricated metal products except machinery and equipment	Medium-High	1170	132
C	22	Manufacture of rubber and plastic products	Medium-High	886	102
E	38	Waste collection treatment and disposal activities; materials recovery	Medium-High	456	49
A	1	Crop and animal production hunting and related service activities	Medium-High	179	28
D	35	Electricity gas steam and air conditioning supply	Very high	1481	218
C	24	Manufacture of basic metals	Very high	1093	144
C	20	Manufacture of chemicals and chemical products	Very high	1040	138
C	23	Manufacture of other non-metallic mineral products	Very high	725	87
C	19	Manufacture of coke and refined petroleum products	Very high	161	20
H	51	Air transport	Very high	16	7
B	6	Extraction of crude petroleum and natural gas	Very high	6	2
B	5	Mining of coal and lignite	Very high	2	1

Table A.5: Emission-relevant sectors in the regression sample

B Robustness

This section evaluates the robustness of the baseline findings reported in Table 3. The baseline specification relates borrower carbon emissions to lenders' probability of default assessments while controlling for borrower characteristics and including creditor and sector fixed effects. Although the baseline results are economically and statistically significant, they may be sensitive to sample construction choices, assumptions regarding the dependence structure of the data, or the fixed-effects specification.

To assess the stability of the results, we conduct three complementary robustness exercises. First, we examine the sensitivity of the estimates to the treatment of highly connected borrowers by varying the cap on the number of lender relationships per borrower-year and by comparing the baseline sample to alternative sample definitions. Second, we investigate whether statistical inference depends on the choice of clustering structure by estimating standard errors under a range of alternative clustering schemes. Third, we evaluate the role of unobserved heterogeneity by re-estimating the baseline specification under alternative fixed-effects structures, including year and borrower-country fixed effects.

Across all robustness exercises, the estimated effects of both Scope 1 and Scope 3 emissions remain stable in sign, magnitude, and statistical significance. Taken together, the results suggest that the baseline findings are not driven by a particular sample construction rule, clustering assumption, or fixed-effects specification.

B.1 Robustness to alternative sample trimming

Our baseline sample restricts the maximum number of lender relationships observed for a borrower in a given year to five. This trimming procedure is intended to limit the influence of highly connected borrowers, which may otherwise receive disproportionate weight in the lender–borrower panel. A potential concern is that the estimated relationship between carbon emissions and lenders' probability of default (PD) assessments is driven by this sample selection choice. To assess the sensitivity of the results, we re-estimate the baseline specification from Table 3 using two alternative sample definitions. First, we relax the trimming rule and allow up to ten lender relationships per borrower-year. Second, we remove the cap entirely and retain all borrower–lender observations. In each case, we estimate the preferred specification, including the full set of firm controls, creditor fixed effects, and sector fixed effects. Table B.1 reports the results for Scope 1 and Scope 3 emissions, respectively. Across all sample definitions, the estimated coefficients remain negative, statistically significant, and economically similar in magnitude to the baseline specification. Increasing the borrower-year lender cap from five to ten has little effect on the estimated relationship between emissions and PD. Likewise, removing the cap altogether produces very similar coefficients. These results indicate that the baseline findings are not driven by the exclusion of highly connected borrowers and are robust to alternative approaches to borrower-hub trimming.

Panel A: Scope 1 emissions

	Cap = 5	Cap = 10	No cap
Scope 1 emissions	-0.024***	-0.023***	-0.026***
	(0.006)	(0.006)	(0.006)
Creditor FE	Y	Y	Y
Sector FE	Y	Y	Y
Observations	20,957	28,355	31,129
R-Squared	0.225	0.239	0.245

Panel B: Scope 3 emissions

	Cap = 5	Cap = 10	No cap
Scope 3 emissions	-0.032***	-0.034***	-0.035***
	(0.005)	(0.006)	(0.007)
Creditor FE	Y	Y	Y
Sector FE	Y	Y	Y
Observations	20,957	28,355	31,129
R-Squared	0.226	0.241	0.246

Table B.1: Robustness to borrower-hub trimming. The table evaluates the sensitivity of the baseline emissions results to alternative restrictions on the maximum number of creditor relationships per borrower-year. Panel A reports results for Scope 1 emissions and Panel B for Scope 3 emissions. The baseline specification corresponds to a cap of five lenders per borrower-year. All specifications include the full set of borrower controls, creditor fixed effects, and NACE sector fixed effects. Standard errors, clustered at the creditor–debtor level, are reported in parentheses.

B.2 Robustness to alternative clustering structures

Our baseline specification reports standard errors clustered at the creditor–debtor level. A potential concern is that inference may be sensitive to the assumed dependence structure in the data, particularly given the panel nature of the lender–borrower relationships. To assess the robustness of statistical inference, we re-estimate the preferred specification from Table 3 under a range of alternative clustering schemes. Specifically, we compare the baseline creditor–debtor clustering with four alternative approaches: two-way clustering by creditor and debtor, clustering at the creditor–year level, clustering by creditor only, and clustering by debtor only. All specifications are estimated using the same baseline sample and include the full set of control variables, creditor fixed effects, and sector fixed effects. Consequently, only the estimated standard errors differ across columns, while the underlying coefficient estimates remain unchanged. Table B.2 reports the results for Scope 1 and Scope 3 emissions. Across all clustering structures, the estimated effects remain economically similar and statistically significant. Although the magnitude of the standard errors varies somewhat across specifications, the core conclusion that higher emissions are associated with lower lender-assigned probabilities of default remains robust. These results suggest that the statistical significance of the baseline findings is not driven by a particular choice of clustering structure.

Panel A: Scope 1 emissions

	Baseline	Two-way	Creditor-Year	Creditor	Debtor
Scope 1 emissions	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***
	(0.006)	(0.006)	(0.003)	(0.004)	(0.006)
Creditor FE	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y
Observations	20,957	20,957	20,957	20,957	20,957
R-Squared	0.225	0.225	0.225	0.225	0.225

Panel B: Scope 3 emissions

	Baseline	Two-way	Creditor-Year	Creditor	Debtor
Scope 3 emissions	-0.032***	-0.032***	-0.032***	-0.032***	-0.032***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.006)
Creditor FE	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y
Observations	20,957	20,957	20,957	20,957	20,957
R-Squared	0.226	0.226	0.226	0.226	0.226

Table B.2: **Robustness to alternative standard-error clustering.** The table evaluates the sensitivity of the baseline emissions results to alternative clustering assumptions for standard errors. The baseline specification clusters standard errors at the creditor–debtor level. Columns additionally report two-way clustering, clustering at the creditor-year level, creditor-level clustering, and debtor-level clustering. Panel A reports results for Scope 1 emissions and Panel B for Scope 3 emissions. All specifications include the full set of borrower controls, creditor fixed effects, and NACE sector fixed effects. Standard errors are reported in parentheses.

B.3 Robustness to alternative fixed-effects specifications

The baseline specification includes creditor and sector fixed effects. To assess whether the estimated relationship between emissions and lender-assigned probabilities of default is sensitive to the treatment of unobserved heterogeneity, we re-estimate the preferred specification under alternative fixed-effects structures. Specifically, we additionally include year fixed effects to absorb aggregate macroeconomic developments and borrower-country fixed effects to account for persistent cross-country differences in credit risk. The most demanding specification combines creditor, sector, year, and country fixed effects. All regressions retain the full set of borrower-level controls and standard errors are clustered at the creditor–debtor level. Table B.3 reports the results for Scope 1 and Scope 3 emissions. The estimated coefficients remain stable across specifications, indicating that the baseline findings are not driven by country-level differences, sector composition, or common time trends.

Panel A: Scope 1 emissions

	Baseline	Year FE	Country FE	Full FE
Scope 1 emissions	-0.024***	-0.025***	-0.024***	-0.025***
	(0.006)	(0.006)	(0.006)	(0.006)
Creditor FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Year FE	N	Y	N	Y
Debtor country FE	N	N	Y	Y
Observations	20,957	20,957	20,957	20,957
R-Squared	0.225	0.229	0.225	0.229

Panel B: Scope 3 emissions

	Baseline	Year FE	Country FE	Full FE
Scope 3 emissions	-0.032***	-0.033***	-0.032***	-0.033***
	(0.005)	(0.005)	(0.005)	(0.005)
Creditor FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Year FE	N	Y	N	Y
Debtor country FE	N	N	Y	Y
Observations	20,957	20,957	20,957	20,957
R-Squared	0.226	0.230	0.226	0.230

Table B.3: Robustness to alternative fixed-effects specifications. The table evaluates the sensitivity of the baseline emissions results to alternative fixed-effects structures. The baseline specification includes creditor and NACE sector fixed effects. Columns additionally include fiscal-year fixed effects, debtor-country fixed effects, or both. Panel A reports results for Scope 1 emissions and Panel B for Scope 3 emissions. All specifications include the full set of borrower controls. Standard errors, clustered at the creditor–debtor level, are reported in parentheses.