Capital Requirements and Carbon Emissions: Climate Misalignment in Prudential Regulation?

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Abstract

This paper investigates whether prudential regulations, specifically Pillar I capital requirements, are apt to mitigate climate-related risks in the financial system. We use a novel dataset that combines granular bank-firm lending data from the European Central Bank's AnaCredit with firm-level financial and carbon emissions data. Using various econometric specifications, we examine the relationship between firms' carbon emissions and banks' capital charges. We find that firms with higher absolute emissions and greater emission intensity are associated with lower capital charges, even within the same sector. Firms in high-emitting sectors – such as agriculture, electricity, and oil and gas – are associated with lower capital charges, while renewable energy firms are associated with higher capital charges. We show that this may result in lower-carbon borrowers facing higher interest rates while lenders achieve reduced risk-adjusted returns when financing lower-carbon borrowers. We argue that the current design of Pillar I capital requirements and the characteristics of low-carbon firms may increase their cost of funding and reduce access to finance.

Keywords: Climate Finance, Prudential Regulation, Financial Regulation

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

1 Introduction

Prudential regulation has become a cornerstone of the modern financial system, particularly following the global financial crisis. Frameworks such as capital requirements are designed to enhance the resilience of financial institutions and safeguard systemic stability. Pillar I capital requirements typically rely on lenders' internal models to estimate borrowers' risk parameters, improving the risk sensitivity of regulatory capital and helping to limit moral hazard. However, this model-based approach may not be aligned with other policy objectives such as reducing the exposure of the financial system to climate-related risks. Growing concerns about climate-induced financial instability and stranded assets have prompted academics and financial regulators to propose policies aimed at – directly or indirectly – catalysing the green transition. In recent years, financial policies focused on mitigating climate-related risks – such as climate stress testing and disclosure – have gained traction. Yet, a critical and often overlooked question in this debate is whether the underlying structure of Pillar I capital requirements is suited to such objectives.

This paper shows that the structure of Pillar I capital requirements is not conducive to a reduction in climate-related risks in the financial system. The literature that studies the macroeconomic effects of model-based regulations shows how these frameworks have real effects because they affect risk premia and firms' cost of capital[1]. Internal risk models used under the Internal Ratings-Based (IRB) approach – which underpin capital requirements in Basel III/IV frameworks – often rely on historical data to estimate borrowers' risk and may fail to capture forward-looking climate-related risks[2]. This can affect credit allocation by favouring high-emitting sectors/firms whose past financial risk may have been lower compared to some emerging low carbon sectors/firms – such as renewable energy – contrary to the objectives of mitigating climate-related risks.

We empirically examine the relationship between borrower-level carbon emissions and lenders' capital requirements, as proxied by lenders' probability of default (PD) estimates of borrowers. We combine granular supervisory data from the European Central Bank's AnaCredit database – which records detailed lender–borrower exposures and lenders' PD

[1] See, for example, Gropp et al. (2019); Benetton et al. (2021)

[2] As evidenced by a recent body of literature. For a survey refer to Monasterolo (2020)

estimates of borrowers – with firm-level financial information from Bureau van Dijk's Orbis and carbon emissions data from S&P Trucost. The resulting panel covers over 7,725 borrowers and 104 lenders across the euro area between 2019 and 2023. These data allow us to investigate how lenders' internal risk assessments vary with borrowers' environmental performance and exposure to climate-related risks.

We find that high-carbon borrowers are systematically assigned a lower probability of default under the Pillar I framework. This negative relationship between emissions and capital requirements is robust across different measures of carbon performance – including absolute and intensity-based emissions – and persists both across and within sectors. In other words, even among firms engaged in similar activities, those operating with lower carbon intensity tend to receive higher capital charges. Further analyses confirm the consistency of this pattern. Across sectors, and particularly within the energy industry carbon-intensive firms such as oil and gas producers are assigned a 10% lower probability of default compared to renewable energy generators. When comparing environmental ratings, we find that – while better ESG scores are associated with lower capital charges – higher emissions are not, suggesting a divergence between how banks integrate general sustainability indicators versus direct measures of carbon risk. We also document that high-carbon borrowers face lower loan spreads and yield higher risk-adjusted returns for banks, suggesting that internal risk assessments may indeed affect pricing and capital allocation to low-carbon sectors/firms.

Our findings provide empirical evidence of a possible misalignment between prudential regulation – specifically Pillar I capital requirements – and climate policy objectives. Lenders' model-based estimates of risk systematically associate higher carbon emission borrowers with relatively lower estimates of risk – and consequently capital requirements – thereby favouring high-carbon borrowers in capital allocation. This dynamic not only undermines the financial system's ability to support the net-zero transition, but may also reinforce the financing of high-carbon sectors/firms exacerbating climate-related risks in the financial system. Our results highlight how current regulatory frameworks inadvertently disincentivize climate-aligned lending in contrast with both central banks' and financial supervisors' policies – such as those on prudential transition planning and climate risk management – as well as broader government climate objectives. Our paper

underscores the need to ensure that risk models incorporate forward-looking climate risks rather than primarily focus on backward-looking assessments.

This paper makes three main contributions. First, it provides the first empirical evidence that Pillar I capital requirements may not be conducive to a reduction in climate-related risks in the financial system. Second, we document a divergence from market-based evidence: whereas financial markets generally associate higher carbon intensity with greater credit risk (Engle, 2024; Delis et al., 2024; Altavilla et al., 2024), lenders' internal models tend to assign lower probabilities of default to such borrowers. This divergence may be – at least partially – explained by how Basel rules require to calculate capital requirements. Third, our findings have direct policy relevance, highlighting the importance of ensuring that prudential frameworks incorporate forward-looking assessments of climate-related risk rather than relying solely on historical data that may underestimate transition exposures.

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 channeling capital from savers to borrowers, thereby supporting investment, consumption, and long-term economic development. A well-functioning financial system is essential for macroeconomic stability, and disruptions in credit markets can have negative consequences for households and firms, as evidenced by the global financial crisis (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 strengthened over recent decades to enhance

the resilience of financial institutions and mitigate systemic risk.

Prudential regulation encompasses a set of rules and supervisory practices aimed at ensuring the safety and soundness of the financial system. 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 is the requirement for 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 (PD) – based on historical data (Dewatripont and Tirole, 1994).

The macroeconomic implications of capital regulation have been widely debated. 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). Empirical studies have shown that changes in capital requirements can significantly affect banks' behavior. 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.

Despite this extensive literature, relatively little is known about how capital requirements influence the allocation of credit across sectors, particularly in the context of the low-carbon transition. This is a critical gap, as achieving net-zero emissions will require a substantial reallocation of financial resources from high-carbon to low-carbon sectors and climate physical and transition risk may have implications for financial stability (Battis-

ton et al., 2017). Relatedly, it is also unclear whether the current design of prudential regulations is apt to mitigating climate related 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). However, Oehmke and Opp (2022) 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, their effectiveness in redirecting capital flows toward green investments remains uncertain[3].

Beyond regulatory proposals, a related strand of work has examined how climate-related risks affect the allocation and pricing of credit more broadly, shedding light on whether financial markets and banks already incorporate transition exposures into lending decisions. Using syndicated loan data, Delis et al. (2024) 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, and that monetary policy affects banks' willingness to lend to carbon-intensive firms. At the systemic level, Jung et al. (2025) introduce the CRISK measure to quantify financial institutions' exposures to climate transition shocks, while Jung et al. (2024) highlight that US banks' loan portfolios remain concentrated in transition-sensitive sectors. Taken together, this evidence suggests that higher emissions and greater transition exposure are generally associated with higher financing costs and increased systemic vulnerability. For a comprehensive overview, de Bandt et al. (2025); Giglio et al. (2021); Edmans and Kacperczyk (2022) review the expanding literature on how climate risks affect banks' balance sheets, credit risk, and stability.

Yet, these studies primarily rely on market-based indicators such as loan spreads, bond

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

yields, or systemic risk measures. Much less is known about how climate-related risks are incorporated into the prudential framework itself, where banks' internal risk models play a central role in determining capital requirements. A largely overlooked question is whether the use of backward-looking IRB models may create frictions that reinforce carbon-intensive investment patterns. Under this approach, banks estimate through-the-cycle probabilities of default (PDs) using historical default data, which may not adequately capture the emerging risks associated with climate change or the transition to a low-carbon economy. As a result, firms in traditionally stable but high-emitting sectors may be assigned lower capital charges, while low-carbon firms, which lack long credit histories or operate in newer industries, may face higher charges. This potential misalignment between prudential regulation and climate policy objectives raises questions about whether the current framework unintentionally favors high-carbon incumbents and constrains the reallocation of credit needed for the net-zero transition.

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. 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 as more data becomes available. These regulatory directives highlight both the urgency and the complexity of aligning prudential regulation with climate objectives, and they underscore why understanding how banks' internal models currently treat high- versus low-carbon firms is of first-order importance.

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 and lenders' estimates of borrower-level Probability of Default (PD) – as the main driver of capital charges. PD and capital charges affect borrowers' cost of credit (i.e., lenders charge higher interest rates to borrowers with higher PDs) and access to finance. Hence, if emissions are negatively associated with PDs, low-carbon borrowers may be at disadvantage compared to high-carbon borrowers and banks may be incentivized to lend to such 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 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[4]. 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

[4]We focus on larger banks and manually check that those use internal based models as opposed to the standardized approach

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 and therefore the 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 about 9000 with AnaCredit. 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 to avoid smaller banks which mostly use the standardized approach[5]. The second filter is to ensure that each bank in our sample has at least 20 firms with carbon emissions every year. This because smaller borrowers may not be captured in S&P's Trucost. Our final dataset is a panel of lender-borrower-year and covers from January 2019 to December 2023 for a total of 5 years. We select this period because only from 2019 data from Anacredit is deemed comprehensive[6]. Table 6 provides some descriptive statistics.

3.2 Empirical Specification

We begin by examining the relationship between firm-level (borrower-level) carbon emissions and the regulatory risk weights assigned by banks (lenders) through their Probability of Default (PD) estimates[7]. Specifically, we ask whether borrowers with higher emissions are systematically assessed as less risky (i.e., with lower PD), all else equal, hence benefitting from lower capital charges. This is important because, in turn, capital charges affect the interest rate applied to borrowers (see Figure 1 and Table A3).

Our first empirical specification focuses on estimating the correlation between banks'

[5]The standardized approach is a simplified methodology to estimate capital charges without relying on banks' internal models. Due to the higher average capital charges, this method is mostly used by smaller banks with lower economies of scale to implement and maintain the IRB approach

[6]See Reghezza et al. (2022)

[7]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 considered as one of the main drivers.

estimates of borrower-level PDs and borrower-level emissions, while controlling for lender-specific modeling practices and time-specific macroeconomic conditions. Since PDs are assigned by banks using internal models, and since these models can vary across institutions and evolve over time, we include lender and year fixed effects. This allows us to isolate the within-year, within-lender variation in PDs across borrowers. Formally, we estimate the following model:

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

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, accounting for time-invariant differences across lenders, such as internal risk modeling practices. The year fixed effects δ_t absorb macroeconomic shocks and other systematic time-varying factors, including changes in the regulatory environment. The variable $Emissions_{i,t}$ measures the carbon profile of borrower i in year t, and can represent either absolute emissions (measured in metric tons of CO_2 equivalent) or emission intensity (emissions per Euro of revenue). We consider multiple operationalizations using Scope 1, Scope 2, and Scope 3 emissions and classifications of high/low-emitting[8]. Finally, $\varepsilon_{i,l,t}$ is an idiosyncratic error term. Standard errors are clustered at the debtor level to account for serial correlation in firm risk characteristics.

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 observable dimensions of a firm's risk profile that banks may already factor into their

[8]Scope 1 emissions refer to direct greenhouse gas (GHG) emissions from sources owned or controlled by the firm, such as combustion in owned boilers or company vehicles. Scope 2 emissions are indirect emissions associated with the consumption of purchased electricity, steam, heat, or cooling. Scope 3 emissions capture all other indirect emissions that occur across the value chain, including those from upstream suppliers and downstream users. These include emissions from purchased goods and services, waste disposal, business travel, and product use.

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 effort or transition plans.

Finally, we also adopt alternative classifications of high- versus low-emitting borrowers. First, following Giannetti et al. (2023), 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 Refinitiv and MSCI (TBD). Refinitiv's E-score reflects a firm's environmental performance, while MSCI's score captures its 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.

4 Results

4.1 PD-emissions relationship

We start by providing some descriptive analysis of the drivers of the estimates of the Probability of Default (PD). Table A1 shows the results of a regression between banks' estimates of PD and borrowers' financial characteristics. Overall, except for country-specific factors, firms with worse financial performance – in terms of solvency, liquidity, and financial margins – are associated with higher Probability of Default. Specifically, the table shows a negative and statistically significant relationship between the PD and Cash flow as percentage of Operating revenue (cfop), Earnings before interest and taxes as percentage of Operating revenue (etma), Total assets (toas), Net income as percentage of Total assets (roa), and Shareholders funds as a percentage of total assets (solr). We also find that the country of the borrower explains the probability of default with France and Spain having higher PD relative to Germany and Italy. The country of borrower explains the largest part of PD differentials followed by Total assets – as a proxy of size – Shareholders funds as a percentage of total assets, and Earnings before interest and taxes as percentage of Operating revenue. These results are not surprising as banks' models rely on similar borrower-level characteristics to estimate the PD and provide some descriptive evidence of some of its drivers.

We then turn to the main analysis studying the relationship between capital requirements and carbon emissions. In our main empirical specification, we run a regression between lenders' estimate of borrowers' Probability of Default and borrowers' carbon emissions. We test different combinations of this relationship in terms of *A.* absolute emissions (i.e., total emissions) and *B.* emission intensity of revenues (i.e., tonnes of CO2 per million EUR of revenue). We focus on results without controlling for any firm-specific characteristics first and then turn to an analysis which shows our results keeping all else being equal – including borrowers' characteristics. We then test this relationship unconditionally and conditional on the sector of the borrower. This is important because it allows us to differentiated between *1.* firms with activities in more/less emitting sectors (e.g., Oil and Gas) and *2.* firms with the highest emissions within their sector (e.g.,

Manufacturer of sport cars) or those that emit less relative to their economic activity and test alternative hypotheses.

Unconditional results

We start by assessing the relationship between carbon emissions and capital requirements. We first use Scope 3 emissions because representing the largest source of emissions of firms[9]. In Panel A of Table 2, we show a negative and statistically significant relationship between borrowers' Scope 3 absolute emissions and lenders' estimates of borrowers' Probability of Default (PD). Borrowers with absolute carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 2.2% lower (higher) by lenders on average (Panel A: 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 3 carbon emissions, on average. In Table 2, we also find consistent results for Scope 2 emissions, but not significant results for Scope 1 emissions[10].

Absolute emissions could be a first proxy of transition risk, but emission intensity – i.e., absolute emissions scaled by some size factor – is generally considered a better measure (Bolton and Kacperczyk, 2021). Indeed, absolute emissions is the product of emission intensity and the size of the firms. For this reason, it tends to load more for larger firms. On the opposite, emission intensity allows to have a relative measure of how emitting a company is. In Panel B of Table 2, we show a negative and statistically significant relationship between Scope 3 emission intensity of revenues and lenders' estimates of Probability of Default (PD). Borrowers with carbon emission intensity of revenues one standard deviation higher (lower) than the mean are assigned a PD about 1% lower (higher) by lenders on average (Panel B: Column 1). This result is consistent with our finding on absolute emissions and indicates that banks tend to assess as riskier firms with lower carbon emissions. Using emission intensity we also find that firms with higher

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

[10]In the subsequent paragraphs of this section, we will deep dive into some specific sectors where Scope 1 emissions are of particular interest (e.g., Power Generation).

scope 1 emission intensity are associated with lower PD. Figure 2, further corroborates the above findings. Borrowers in the higher quintile of emission intensity are associated with higher PD compared to those at the bottom quintile.

These findings indicate that banks assess lower-carbon firms as riskier. This assessment could influence these firms' access to credit and cost of funding — an issue we will revisit later. However, a key question arises: are these differences in risk assessments driven by idiosyncratic distinctions between low- and high-carbon borrowers that lenders' models accurately capture, or are they the result of biases in those models? This distinction is crucial, as it shifts the focus either to the regulatory framework or to inherent structural differences between firms with varying carbon profiles. Our results could reflect one of two possible scenarios: (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 scenario is true, it suggests a potential bias in banks' internal risk models that favors high-carbon firms. If the second is true, then the observed outcomes may simply reflect underlying structural differences in the financial creditworthiness of these firms.

To test our hypotheses, we add to the regression some covariates which could explain the creditworthiness of firms. Controlling for borrowers' idiosyncratic characteristics allows us to study if all else being equal the negative relationship between carbon emissions and capital charges holds. In Table 2, we show that the coefficient remains negative and statistically significant, although the magnitude of the effect diminishes (Panel A: Column 2). Similarly, we also test the relationship between the PD and carbon emission intensity controlling for borrowers' idiosyncratic characteristics. In Table 2, we show consistent results. All else being equal, borrowers with scope 3 carbon emission intensity of revenues one standard deviation higher (lower) than the mean are assigned a PD about 1% lower (higher) by lenders on average (Panel B: Column 2). This suggests that idiosyncratic characteristics could explain part of the negative relationship, but other factors may be at play[11]. Specifically, these results do not rule out neither hypothesis 1 nor 2 and a combination of factors seems the most likely explanation.

[11] An alternative interpretation could be that we are not able to fully capture the differences in creditworthiness between low and high carbon firms.

Sector-level analysis

Our results show a negative relationship between carbon emissions and the probability of default of firms estimated by banks regardless of their economic activity. However, firms may be in some high-emitting sectors – such as Oil and Gas, Electricity, Transport – or in low-emitting sectors. An interesting related question is the relationship between capital requirements and the relative emission profile of firms within their respective sector. For example, Power Generation companies are generally highly emitting, but there is heterogeneity within the sector with some renewable energy players with low emissions and coal producers with high emission, for example. This is important because it allows us to understand better if the economic activity explains differentials in capital charges or our results hold regardless of the sector the company operates in. For this reason, we next study whether our results hold within specific sectors.

In Table 2, 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 remain of similar magnitude to those not controlling for industry fixed effects. Borrowers with absolute carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 2.2% lower (higher) by lenders on average (Panel A: Column 3). The same result holds controlling for firms idiosyncratic characteristics (Panel A: Column 4). Within sector results are also similar for emission intensity of revenue. In Panel B, we show that borrowers with carbon emission intensity of revenues one standard deviation higher (lower) than the mean are assigned a PD about 1% lower (higher) by banks on average, in both cases of controlling for idiosyncratic factors or not (Panel B: Column 3 and 4). Similarly to before, the coefficients become smaller when controlling for borrowers' idiosyncratic characteristics, but remain significant indicating the the differentials in capital charges may not be fully explained by economic activity.

These results provide a more nuanced perspective to our overarching results. Risk-based estimates underpinning capital requirements may be negatively correlated with carbon emissions, both in terms of absolute emissions and emission intensity and controlling for idiosyncratic characteristics of borrowers and not. But these relationship may also be present in relative terms within specific sectors. Not only firms with lower emis-

sions 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. This may be detrimental to ensuring that capital requirements incorporate (and contribute to mitigating) climate related risks and it may disadvantage low carbon firms.

We also test if the results vary across different lenders depending on their emission intensity. We calculate the emission intensity of assets of the lender – defined as the sum of its borrowers' emissions divided by its total lending – and construct a dummy variable equal 1 if the lender's emission intensity is lower than the median (labelled "Low carbon lenders") or lower than the 10th percentile (labelled "Green lenders"). Although imperfect, this approach allows us to interact the dummy variable with absolute emissions and emission intensity[12]. In Table 3, we show that the interaction term between Scope 1 absolute emissions and Scope 1 emission intensity is positive and significant for both low carbon and green lenders. This indicates that lower carbon lenders' estimates of probability of default offset the overall negative relationship found in the full sample. The interaction term is also significant when controlling for sector fixed effect, although the main variable coefficient becomes not significant. In unreported results we do not find statistically significant results for Scope 3 emissions and for the interaction with a dummy of "brown lenders" (i.e., those with emission intensity of assets higher than the 90th percentile).

We then analyse differences between sectors. We follow Giannetti et al. (2023) and classify as high emitting sectors *1.* the highest contributors to the overall emissions in Europe (i.e., those with absolute emissions above the median)[13] and *2.* those that have the highest emission intensity defined as sector's emissions divided by the Gross Value Added (GVA) of the sector (i.e., those with absolute emissions above the median). We classify as the highest absolute emitting sectors (1): Agriculture, forestry and fishing, Manufacturing, Electricity, gas, steam and air conditioning supply, Transportation and storage. We classify the highest emission intensity sectors (2): Electricity, gas, steam

[12]We recognise that the crude sum of borrowers' emissions is not a perfect measure of lenders' financed emissions as defined by industry standards and methodologies (e.g., Partnership for Carbon Accounting Financials, Net Zero Banking Alliance), but it allows to broadly rank lenders depending on emissions associated with their lending.

[13]Using data from Eurostat

and air conditioning supply; Agriculture, forestry and fishing Water supply; sewerage, waste management and remediation activities; and Mining and quarrying. 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 absolute emission sectors and highest emission intensity sectors are associated with lower Probability of Default. Borrowers in these sectors are associated with between 3% and 3.5% lower PD (Panel A: Columns 1 and 3). When controlling for borrowers' idiosyncratic characteristics, the results for absolute emissions become not significant while the magnitude for emission intensity doubles to about 7%. We then turn to assess individual sectors focusing on some of the most polluting: Agriculture, Electricity, Mining, and Transport. 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 the agriculture and the electricity sectors are negative and statistically significant. Borrowers in the Agriculture sector are associated with 12% lower PD while borrowers in the Electricity sector are associated with a 8% lower PD. The results are not statistically significant for the Mining and Transport sectors. These results align with previous evidence showing that firms in some of the most emitting sectors may be associated with lower capital requirements.

Energy sector analysis

Mitigating climate change will in large part depend on decarbonizing the energy sector and transitioning to clean electricity. The energy sector is responsible for around two-thirds of emissions[14]. Often the debate is between the continuous use of fossil fuels or the shift to renewable energy. To test the differential between these two alternative energy sources, we compare firms operating within the Oil and Gas industry with firms operating in Solar and Wind production. 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

[14]Source: Our World In Data

(Mining support service activities), and C19 (Manufacture of coke and refined petroleum products) and Solar and Wind firms those in the more granular NAICS v2017 codes 221114 (Power generation, solar electric) and 221115 (Power generation, wind electric). In Panel B of Table 5, we show that Oil and Gas are associated with about 10% lower PD estimates compared to the overall sample while we do not find any statistically significant difference with Solar and Wind firms. This result aligns with out previous results whereas firms with high scope 3 emissions are associated with lower capital charges.

Previous results show that the electricity sector – in aggregate – is associated with lower capital charges. However, the sector is highly heterogenous. To better investigate this heterogeneity we limit our sample to electricity companies[15] and test the relationship between capital requirements and borrower's Scope 1 carbon emissions. In this analysis we focus specifically on Scope 1 emissions because it allows us to discriminate the emission profile of electricity generation of firms directly (i.e., those arising from the generation of electricity). In Panel A of Table 5, we show that – within the electricity sector – borrowers' scope 1 emissions – both absolute and emission intensity – are negatively associated with lenders' estimate of borrowers' Probability of Default. Borrowers with emission intensity one standard deviation higher (lower) than the mean are assigned a PD 2% lower (higher) by banks on average. Similarly, borrowers with absolute carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 2% lower (higher) by banks on average. However, in this specific case the results turn not significant when we controlling for idiosyncratic firm characteristics. This may indicate that low carbon firms have characteristics that lead internal models to assess them as riskier. For example, renewable energy may be intrinsically riskier than other forms of energy productions (without considering transition risks) due to their higher leverage.

Other sustainability factors

In this section, we also explore the relationship between capital charges – as proxied by Probability of Default estimates – and other metrics. We first start with ESG ratings from two major providers: Refinitiv and MSCI. We select these two providers because of their complementary measurements. Refinitiv's rating reflects a firm's ESG performance

[15] Those classified in the NACE sector D: Electricity, gas, steam and air conditioning supply

while MSCI's rating captures its exposure to ESG risks[16]. We also assess whether lenders estimate lower capital charges if borrowers have a net zero target.

In Table 6, we show a negative and statistically significant relationship between lenders' estimates of borrowers' Probability of Default for both Refinitiv (Panel A) and MSCI ESG (Panel B) ratings. Differently from emissions, higher ESG ratings mean better ESG performance and lower ESG risk. Hence, while for carbon emissions we find that highest emitting borrowers are consistently associated with lower PDs, in this case, better ESG performing borrowers are associated with lower PDs. The coefficients are both economically and statistically significant, except for Refinitiv when controlling for sector fixed effects and including borrowers' characteristics controls.

In Table A2 in Appendix, we also show the detailed breakdown for the Environmental, Social, and Governance pillars for both Refinitiv and MSCI ESG ratings. The results are negative and statistically significant for E and G for Refinitiv, but only negative and statistically significant for S for MSCI. This implies that the negative association with MSCI ESG rating is mostly driven by its S components while for Refinitiv both E and G components. While this result seems to show that capital charges are incorporating positive environmental externalities – as opposed to ESG risks – this per se does not invalidate our previous findings that are specific of climate change. Unfortunately, we cannot assess all individual components driving the association between the Refinitiv E score and PDs, but the reader should note that climate change is only one of the multiple environmental components included in the score (e.g., pollution prevention, nature loss).

We then turn to assess if borrowers with net zero targets are associated with lower capital charges. Net zero targets may lead to emission reductions and associated positive environmental externalities and climate related risk reductions. In Table 6 (Panel C), we show the results of the regression between the lenders' estimates of borrowers' Probability of Default and a dummy variable equal one if the borrower has a net zero target. We find that borrowers with net zero targets are associated with lower PDs. The coefficient is negative and statistically significant. Borrowers with a target are associated with about 11% lower PDs, however, the magnitude decreases when introducing controls and in one

[16]See `https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores` and `https://www.msci.com/data-and-analytics/sustainability-solutions/esg-ratings`

instance the coefficient becomes not significant.

Despite some sustainability considerations such as ESG ratings – specifically some of their individual components – and net zero targets seem to be considered favourably in capital requirements, the largest part of the evidence shown in this section – and specifically carbon emissions – points towards lower capital requirements for the least environmentally friendly borrowers – specifically high-emitting sectors and firms. This may have consequences on low carbon firms access to finance and cost of credit on which we turn next.

4.2 Implications of the PD-emissions relationship

We now turn to the implications of this differentials before turning to some possible explanations for the differences in estimates of capital weights. We start by assessing whether carbon emissions are associated with higher interest rates charged by banks to firms. In Table 7, we show a negative and statistically significant relationship between the spread over the risk-free rate charged to borrowers by lenders and borrowers' absolute carbon emissions and emission intensity. Borrowers with scope 3 emission intensity one standard deviation higher (lower) than the mean are associated with 1.7% lower (higher) interest rates by banks, on average (Panel B: Column 1 and 3). Similarly, borrowers with scope 3 absolute carbon emissions one standard deviation higher (lower) than the mean are assigned a PD 3.7% lower (higher) by banks on average (Panel A: Column 1 and 3). Similar results hold for absolute emissions when controlling for sector fixed effects but the coefficient turns not significant for emission intensity (Panel A and B: Column 2 and 4). Instead the results remain negative and statistically significant regardless of the specification for Scope 1 emissions intensity and absolute emissions.

Although these results may arise from various factors including the appetite of banks to lend to different sectors, it is likely that they are – at least in part – driven by differentials in risk assessments. Firstly, as we show in Figure 1, there is a correlation between probability of default and interest rates charged to firms by banks[17]. This is also aligned with anecdotal evidence and regulatory guidance on incorporating risk

[17]The coefficient of the regression between PD and spread is positive and statistically significant (see Table A3).

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 capital charges for low emitting firms result in higher cost of funding for those borrowers. However, lower carbon firms' higher interests may be appealing for banks increasing their access to finance.

To further understand whether higher capital charges – and interest rates – may (dis)incentivize banks to lend to low-carbon firms as opposed to high-carbon firms, we calculate the risk-adjusted return of banks by dividing the interest rate charged to borrowers by the Probability of Default (ReturnPD). This metric measures the unit of remuneration for each unit of estimated risk which is arguably the metrics that lenders should target to maximize their profits (rather than the absolute level of interest rates). In fact, in a general equilibrium framework, purely maximizing interest charged to borrowers may steer lending towards high risk borrowers and increase impairments. Instead, lenders in line with traditional portfolio management theory aim to maximize risk-adjusted returns.

In Table 8, we replicate our previous results with our measure of risk-adjusted returns. We show a positive and statistically significant relationship between *ReturnPD* and both absolute emissions and emission intensity. Borrowers with scope 1 absolute carbon emissions one standard deviation higher (lower) than the mean are assigned a risk-adjusted return between 1.4% and 3.1% higher (lower) by banks on average, although the results are not significant within industry. The results are even stronger for scope 1 emission intensity with value ranging from 1.5% and 5.5% and they remain significant even with industry fixed effects[18]. This indicates that banks obtain higher returns per unit of capital charges/ per unit of risk for carbon intensive and high-carbon firms compared to low carbon firms. In turn, lower carbon firms may be a less appealing financing opportunity for banks decreasing their access to funding.

[18]In unreported results we also find a negative coefficient for solar and wind firms and a positive coefficient for Oil & Gas, but not statistically significant

4.3 Drivers of the PD-emissions relationship

In the previous section, we have shown a negative relationship between capital requirements and carbon emissions and their implications for firms' cost of funding and access to finance. We have also discussed how the energy sector is one of the most important to decarbonize the economy. We showed that the negative relationship between capital requirements and carbon emissions is particularly salient within the electricity sector and that generally oil and gas firms are associated with lower capital requirements compared to renewable energy firms (solar and wind). In this section, we try to shed light on some of the possible drivers of this differences and discuss whether these are an artifact of the structure of the regulation or representative of the real underlying risk of firms. We select a sub-sample in our data focusing on Oil and Gas firms and Renewable energy firms and we conduct some analysis to study the differentials in some key profitability, solvency, and liquidity ratios that may explain the differentials in creditworthiness. To make our analysis more representative, in this case, we rely on a global sample of firms from Bureau Van Dyck's Orbis.

Table 9 shows that Oil and Gas firms have a better financial situation compared to Renewable energy firms. Oil and Gas firms have on average a 22% higher Interest coverage ratio (IC) – defined as the ratio between Earnings Before Interest and Taxis (EBIT) and interest expenses. Similarly, Oil and Gas firms have on average a 48% higher solvency ratio (SOLR)- defined as the ratio of total assets over total liabilities. IC and SOLR are two key solvency measures assessed by financial risk models to estimate the probability of default of borrowers. Turning to liquidity, Oil and Gas firms seem to be better also from a liquidity perspective. Table 9 shows that Oil and Gas firms have on average 23% higher current ratio compared to Renewable energy firms – defined as ratio of current assets over current liabilities. These are only some of the variables considered by risk models for assessing the Probability of Default of borrowers, but our analysis shows clearly that on paper historically Oil and Gas lending has been safer than Renewable energy.

Table 9 shows that Oil and Gas firms are better positioned from a solvency and liquidity perspective. A related question is whether these firms have also better profit margins. We consider two profit 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 we show that Renewable energy companies have generally better profitability margins. On average we find that Renewable energy firms have a 40% higher EBIT margin and 15% higher gross margin compared to Oil and Gas firms. However, while investors may be interested in profitability margins, lenders such as banks pay strong attention to solvency and liquidity ratios – as shown by our analysis on the relationship between PD and financial ratios (Table A1). Hence, while Renewable energy firms may be more profitable, they currently remain less creditworthy for banks. This may be due to their unique capex-intensive structure vs the opex-intensive model of Oil and Gas firms, but our data does not allow to explore this key motivation for this differentials, which ultimately may be the unique capital structure required for the two types of businesses[19].

Historically Oil and Gas firms seem to have been safer from a lending perspective compared to Renewable energy. However, one may ask whether the situation has changed throughout time and, more importantly, whether this will change in the future. While we cannot predict the future, this question is important because banks' risk models use long term historical series to estimate the Probability of Default of borrowers. This implies that they may exacerbate path-dependency in the economy by favouring incumbent methods of energy production vs new environmental friendly renewables. Indeed, this seems to be changing. In Table 9, we show that the interest coverage ratio and the current ratio of renewable energy firms is positively correlated with the time component. Perhaps not surprisingly, renewable energy firms are getting more creditworthy with the time. This is in contrast with the current assessments of risk models which may not capture this improving conditions quickly enough due to their long-term perspective[20]. In Table A5 and A6 we show the relationship between carbon emissions and emission intensity respectively and the financial ratios discussed above.

[19]In Table A7, we expand our analysis on a dataset with global firms going back 20 years and including low carbon and high carbon firms (not only Oil and Gas and Renewable energy). The results are generally consistent: high carbon firms have better solvency and liquidity, although they have lower profit margins.

[20]While we acknowledge that out time series only covers five years, our analysis in Table A7 shows consistent results globally and on a longer time frame. The average of low carbon firms liquidity and solvency ratios improves as we use more recent periods.

5 Conclusion

This paper shows that prudential regulations - specifically Pillar I capital requirements - may not be apt to mitigate climate-related risks in the financial system and supporting the financing of the low-carbon transition. We find a negative and statistically significant relationship between lenders' capital charges - estimated with internal rating-based models (IRB) - and borrowers' carbon emissions. This relationship holds within and between sectors, including within the energy and power generation sectors. We show this may be driver of the higher interest rate charged by lenders to lower-emitting firms and the lower risk-adjusted returns achieved by banks for lending to these companies. We discuss that a possible explanation for this phenomenon may reside in the IRB approach's reliance on historical experience to inform risk estimates – which may fail to capture forward-looking risks – and idiosyncratic differences between low-carbon and high-carbon borrowers, especially in the energy sector. Our work calls for further studies on the design of capital requirement frameworks to align with recent central bank and financial supervisor policies aimed at mitigating climate-related risks.

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6 Tables and Figures

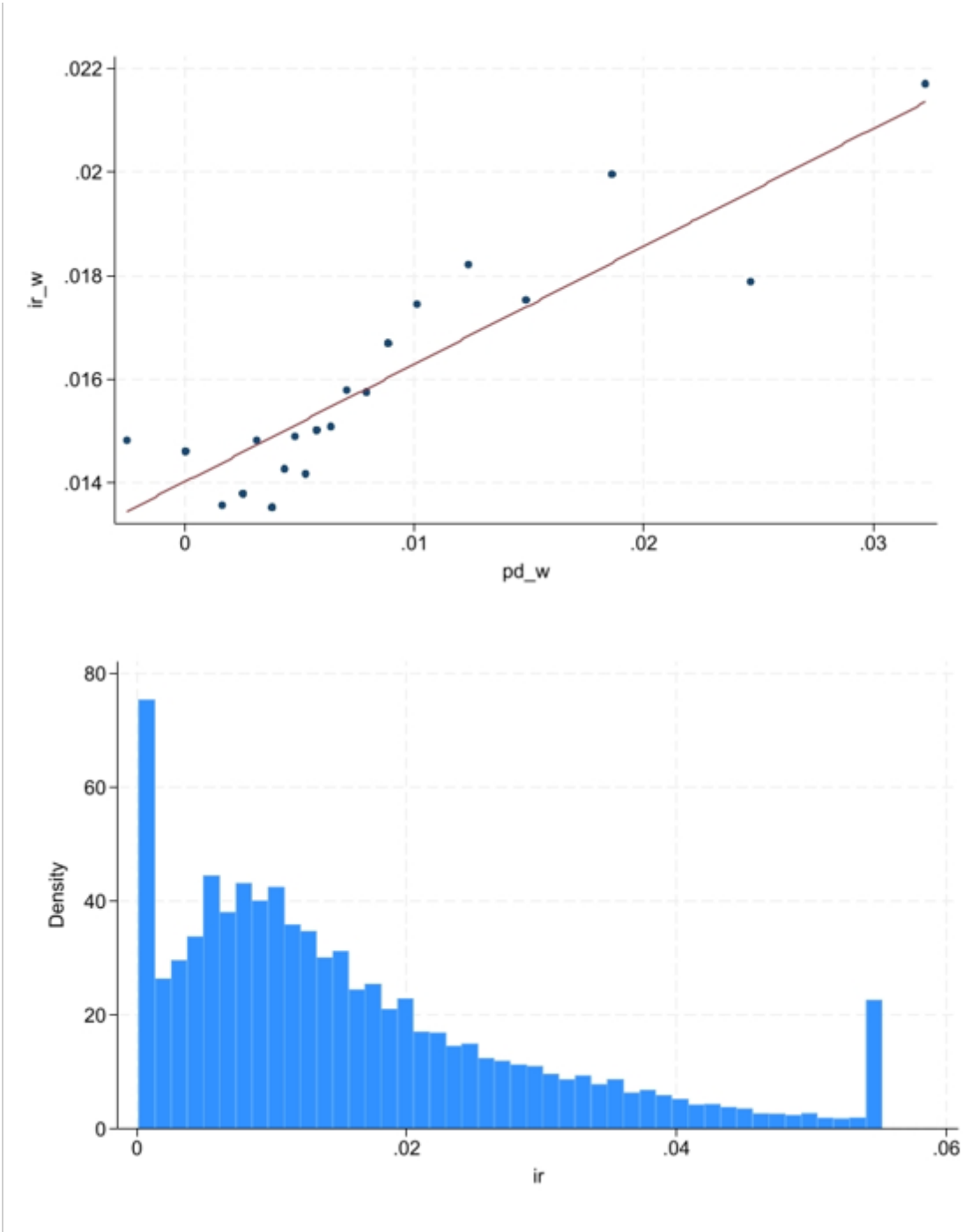


Figure 1: Probability of Default and Interest Rates. Panel A shows the relationship between bank-estimated probability of default (PD) of a borrower and interest rates on loans to the borrower using Binscatter. **Panel B** shows the frequency distribution of interest rates for loans to firms in our sample. Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023.

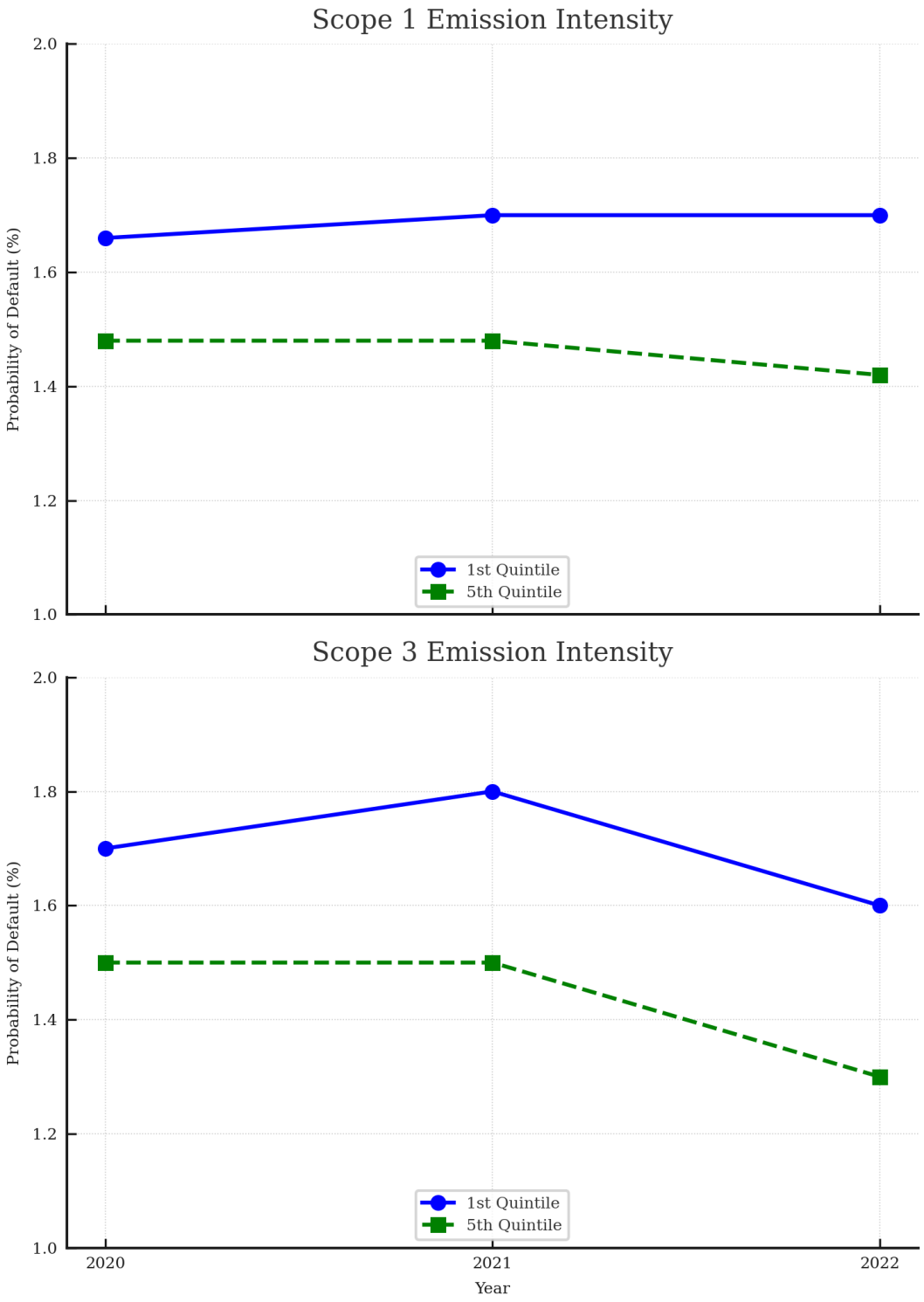


Figure 2: Probability of Default and quintile of emissions. The figure shows the average of lender's estimate of Probability of Default (PD) of borrower by quintile of borrower scope 1 and scope 3 emission intensity of revenue. Years reported from 2020 to 2022 due to low number of observations in 2019 and 2023. Difference in PD between first and fifth quintile for scope 1 emissions 14 basis points (158 and 144 respectively. Difference in PD between first and fifth quintile for scope 3 emissions 18 basis points (160 and 142 respectively.

Panel A: Number of Debtors by Country

	Country debtor				
Country creditor	Germany	Spain	France	Italy	Total
Germany	4,052	32	90	36	4,210
Spain	46	3,236	47	32	3,361
France	43	25	5,821	29	5,918
Italy	40	18	45	5,153	5,256

Panel B: Probability of Default by Fiscal Year

Fiscal Year	Mean	Standard dev	Minimum	Maximum	N
2019	3.78%	16.04%	0%	100%	11,022
2020	4.29%	16.81%	0%	100%	11,535
2021	4.57%	17.12%	0%	100%	13,029
2022	4.65%	17.35%	0%	100%	13,125
2023	4.91%	18.47%	0%	100%	7,907
Total	4.43%	17.11%	0%	100%	56,618

Panel C: Probability of Default by Country

Fiscal Year	Mean	Standard dev	Minimum	Maximum	N
Germany	3.27%	15.11%	0%	100%	15,333
Spain	6.43%	21.96%	0%	100%	253
France	4.86%	17.23%	0%	100%	20,963
Italy	4.84%	18.27%	0%	100%	20,069
Total	4.43%	17.11%	0%	100%	56,618

Table 1: Descriptive statistics. The tables show descriptive statistics for the main variables of interest in our sample. Data from January 2019 to December 2023. **Panel A** shows the number of creditors (lenders) and debtors (borrowers) in the sample for the main countries in our dataset. **Panel B** shows mean, standard deviation, minimum, maximum, and number of observations for the banks-estimates of Probability of Default (PD) by year. Panel C reports the mean, standard deviation, minimum, maximum, and number of observations for the banks-estimates of Probability of Default (PD) by main country of creditor (borrower).

Panel A: Absolute Emissions

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Absolute Emission	-0.0036	-0.0039	-0.0004	0.0015
	(0.0023)	(0.0034)	(0.0026)	(0.0039)
Scope 2 Absolute Emission	-0.0151***	0.0183***	-0.0196***	0.0086*
	(0.0028)	(0.0048)	(0.0031)	(0.0050)
Scope 3 Absolute Emission	-0.0220***	-0.0121***	-0.0228***	-0.0199***
	(0.0028)	(0.0046)	(0.0030)	(0.0048)
Constant	-0.2780***	-0.3020***	-0.2780***	-0.3070***
	(0.0018)	(0.0117)	(0.0018)	(0.0116)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	28,110	12,039	28,107	12,037
R-squared	0.1200	0.2070	0.1460	0.2480

Panel B: Emission Intensity of Revenue

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Emission Intensity	-0.0046**	-0.0027	-0.0036	0.0016
	(0.0020)	(0.0029)	(0.0025)	(0.0037)
Scope 2 Emission Intensity	-0.0025	0.0147***	-0.0043*	0.0119***
	(0.0020)	(0.0032)	(0.0024)	(0.0038)
Scope 3 Emission Intensity	-0.0081***	-0.0075**	-0.0073**	-0.0137***
	(0.0021)	(0.0035)	(0.0031)	(0.0046)
Constant	-0.2790***	-0.3030***	-0.2790***	-0.3100***
	(0.0019)	(0.0116)	(0.0018)	(0.0115)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	28,110	12,039	28,107	12,037
R-squared	0.0630	0.2080	0.1350	0.2480

Table 2: Probability of Default and carbon emissions. The table reports the results of a linear regression between debtors (borrowers)' Scope 1, 2, and 3 carbon emissions and lenders' estimates of Probability of Default (PD). **Panel A** reports results for absolute emissions. **Panel B** reports results for emission intensity of revenues defined as borrower absolute emissions divided by borrower revenues. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, creditor (lender), and NACE sector fixed-effects.

Panel A: Absolute Emissions

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Emission	-0.00950***	-0.00897**	-0.00348	-0.00310
	(0.00350)	(0.00389)	(0.00315)	(0.00354)
S1 Emiss * Low Carbon Dummy	0.0283***	0.0259***		
	(0.00636)	(0.00633)		
S1 Emiss * Green Dummy			0.0577***	0.0455**
			(0.0211)	(0.0207)
	(0.00332)	(0.00342)	(0.00332)	(0.00343)
Constant	-0.270***	-0.270***	-0.271***	-0.271***
	(0.00284)	(0.00278)	(0.00282)	(0.00276)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	Y	N	Y
Controls	Y	Y	Y	Y
Observations	12,039	12,037	12,039	12,037
R-squared	0.207	0.246	0.206	0.245

Panel B: Emission Intensity of Revenue

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Emission Intensity	-0.0110***	-0.00591	-0.00137	0.00290
	(0.00348)	(0.00397)	(0.00282)	(0.00333)
S1 Intens * Low Carbon Dummy	0.0305***	0.0254***		
	(0.00572)	(0.00571)		
S1 Intens * Green Dummy			0.0435***	0.0270*
			(0.0147)	(0.0144)
Constant	-0.270***	-0.271***	-0.271***	-0.272***
	(0.00281)	(0.00275)	(0.00281)	(0.00275)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	Y	N	Y
Controls	Y	Y	Y	Y
Observations	12,039	12,037	12,039	12,037
R-squared	0.207	0.246	0.206	0.245

Table 3: Probability of Default and carbon emissions - Interactions. The table reports the results of a linear regression between debtors (borrowers)' Scope 1 carbon emissions and lenders' estimates of Probability of Default (PD) and the interaction with a dummy indicating if the lender is a "low carbon" or "green" lender. **Panel A** reports results for absolute emissions. **Panel B** reports results for emission intensity of revenues defined as borrower absolute emissions divided by borrower revenues. Low carbon lender defined as lenders with total borrowers' emissions divided by total outstanding loans (lender emission intensity) lower than the median across banks. Green lenders defined as those with an emission intensity lower than the 10th percentile across banks. Control variables included are the same as previous table. Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023.

Panel A: Emissions

	(1)	(2)	(3)	(4)
Total emissions dummy	-0.0304***	-0.00728		
	(0.00328)	(0.00634)		
Emission int dummy			-0.0355***	-0.0695***
			(0.00672)	(0.0126)
Constant	-0.265***	-0.299***	-0.276***	-0.300***
	(0.00193)	(0.0118)	(0.00149)	(0.0116)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	44,367	12,039	44,367	12,039
R-squared	0.113	0.206	0.111	0.208

Panel B: Sectors

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Agriculture Dummy	-0.118**			
	(0.0498)			
Electricity Dummy		-0.0807***		
		(0.0143)		
Mining Dummy			0.00933	
			(0.0968)	
Transport Dummy				0.0234
				(0.0159)
Constant	-0.302***	-0.301***	-0.302***	-0.303***
	(0.0116)	(0.0116)	(0.0116)	(0.0116)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	12,039	12,039	12,039	12,039
R-squared	0.207	0.208	0.206	0.206

Table 4: Probability of Default and emitting sectors. The table reports the results of a linear regression between debtors (borrowers)' sector and lenders' estimates of Probability of Default (PD). **Panel A** reports results for sectors with highest aggregate-level emissions or highest emission intensity. Total emissions dummy is equal 1 if debtor (borrower) is in one of the following sectors: if Agriculture, forestry and fishing, Manufacturing, Electricity, gas, steam and air conditioning supply, Transportation and storage. Emission intensity dummy is equal 1 if the debtor (borrower) is in one of the following sectors: Electricity, gas, steam and air conditioning supply Agriculture, forestry and fishing Water supply; sewerage, waste management and remediation activities Mining and quarrying. **Panel B** reports the results for individual sectors' dummies. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, and creditor (lender) fixed-effects.

Panel A: Electricity sector

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Scope 1 Emis Intensity	-0.0303***	-0.0117		
	(0.00619)	(0.00872)		
Scope 1 Absolute Emis			-0.0190***	0.00572
			(0.00545)	(0.00668)
Constant	-0.312***	-0.350***	-0.317***	-0.403***
	(0.0195)	(0.0405)	(0.0129)	(0.0263)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	909	484	909	484
R-squared	0.354	0.494	0.359	0.489

Panel B: Energy sector

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Oil and Gas Dummy	-0.104***	-0.152*		
	(0.0227)	(0.0818)		
Solar and Wind Dummy			0.00468	0.0356
			-0.022	-0.0309
Constant	-0.277***	-0.302***	-0.277***	-0.303***
	(0.00146)	(0.0116)	-0.00146	-0.0116
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	44,367	12,039	44367	12039
R-squared	0.111	0.207	0.111	0.206

Table 5: Probability of Default and Energy sector. Panel A reports the results between Scope 1 Emissions - absolute and intensity of revenues - for the electricity sector. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). **Panel B** reports the results of a linear regression between debtors (borrowers)' sector and lenders' estimates of Probability of Default (PD). Sectors considered are either Oil and Gas or Solar and Wind. Dummy defined as 1 if the debtor (borrower) is part of the respective sector or 0 otherwise. Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, and creditor (lender) fixed-effects.

Panel A: Refinitiv ESG Ratings

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Refinitiv ESG	-0.134***	-0.0860*	-0.122***	-0.0457
	(0.0213)	(0.0441)	(0.0222)	(0.0489)
Constant	-0.307***	-0.283***	-0.314***	-0.297***
	(0.0131)	(0.0235)	(0.0136)	(0.0256)
Creditor FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	4,188	1,681	4,186	1,676
R-squared	0.145	0.242	0.209	0.317

Panel B: MSCI ESG rating

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
MSCI ESG	-0.0133***	-0.0220**	-0.0207***	-0.0463***
	(0.00487)	(0.00853)	(0.00526)	(0.0101)
Constant	-0.333***	-0.230***	-0.294***	-0.112**
	(0.0259)	(0.0454)	(0.0279)	(0.0521)
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	3,360	1,329	3,358	1,326
R-squared	0.148	0.245	0.240	0.359

Panel C: Net Zero targets

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Target	-0.121***	-0.0170	-0.113***	-0.0215*
	(0.00630)	(0.0118)	(0.00642)	(0.0121)
Constant	-0.270***	-0.270***	-0.271***	-0.270***
	(0.00149)	(0.00301)	(0.00148)	(0.00296)
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	44,367	12,039	44,364	12,037
R-squared	0.118	0.205	0.141	0.245

Table 6: Probability of Default and ESG factors. The table reports a regression between PDs and **Panel A** Refinitiv ESG ratings, **Panel B** MSCI ESG ratings, and **Panel C** a dummy equal 1 if the borrower has a net zero target. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time and creditor (lender) fixed-effects.

Panel A: Absolute Emissions

	(1)	(2)	(3)	(4)
	Spread	Spread	Spread	Spread
Scope 1 Absolute Emission	-0.0260***	-0.0217***	-0.0247***	-0.0260***
	(0.00562)	(0.00768)	(0.00654)	(0.00897)
Scope 2 Absolute Emission	-0.0130*	0.0186*	-0.0198***	0.00915
	(0.00695)	(0.0108)	(0.00765)	(0.0116)
Scope 3 Absolute Emission	-0.0372***	-0.0261**	-0.0292***	-0.0209*
	(0.00689)	(0.0103)	(0.00751)	(0.0110)
Constant	-0.241***	-0.327***	-0.241***	-0.327***
	(0.00456)	(0.00645)	(0.00454)	(0.00640)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	26,799	11,157	26,796	11,155
R-squared	0.238	0.212	0.250	0.233

Panel B: Emission Intensity of Revenue

	(1)	(2)	(3)	(4)
	Spread	Spread	Spread	Spread
Scope 1 Emission Intensity	-0.0217***	-0.0126*	-0.0215***	-0.0172**
	(0.00535)	(0.00667)	(0.00617)	(0.00845)
Scope 2 Emission Intensity	0.0230***	0.0177**	0.0133**	0.0117
	(0.00530)	(0.00733)	(0.00595)	(0.00873)
Scope 3 Emission Intensity	-0.0177***	-0.00313	0.0143*	0.00890
	(0.00559)	(0.00793)	(0.00767)	(0.0106)
Constant	-0.243***	-0.329***	-0.242***	-0.327***
	(0.00497)	(0.00649)	(0.00454)	(0.00649)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	26,799	11,157	26,796	11,155
R-squared	0.093	0.212	0.246	0.232

Table 7: Interest rates and carbon emissions. The table reports the results of a linear regression between debtors (borrowers)' Scope 1, 2, and 3 carbon emissions and lenders' spread above the risk-free rate. **Panel A** reports results for absolute emissions. **Panel B** reports results for emission intensity of revenues defined as borrower absolute emissions divided by borrower revenues. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, creditor (lender), and NACE sector fixed-effects.

Panel A: Absolute Emissions

	(1)	(2)	(3)	(4)
	ReturnPD	ReturnPD	ReturnPD	ReturnPD
Scope 1 Absolute Emission	0.0238***	0.0549***	0.0147***	0.0320***
	(0.00479)	(0.00691)	(0.00556)	(0.00802)
Scope 2 Absolute Emission	0.0232***	-0.0371***	0.0263***	-0.0245**
	(0.00592)	(0.00976)	(0.00649)	(0.0103)
Scope 3 Absolute Emission	0.00530	-0.0109	0.0138**	0.00828
	(0.00587)	(0.00929)	(0.00637)	(0.00981)
Constant	-0.159***	-0.162***	-0.159***	-0.162***
	(0.00389)	(0.00581)	(0.00385)	(0.00572)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	26,799	11,157	26,796	11,155
R-squared	0.172	0.201	0.191	0.233

Panel B: Emission Intensity of Revenue

	(1)	(2)	(3)	(4)
	ReturnPD	ReturnPD	ReturnPD	ReturnPD
Scope 1 Emission Intensity	0.0139***	0.0316***	0.00806	0.0111
	(0.00442)	(0.00601)	(0.00524)	(0.00755)
Scope 2 Emission Intensity	0.0192***	-0.0225***	0.0151***	-0.0165**
	(0.00438)	(0.00661)	(0.00505)	(0.00780)
Scope 3 Emission Intensity	-0.00372	-0.0140**	0.00115	-0.00200
	(0.00462)	(0.00715)	(0.00651)	(0.00947)
Constant	-0.158***	-0.164***	-0.158***	-0.162***
	(0.00411)	(0.00584)	(0.00386)	(0.00580)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	26,799	11,157	26,796	11,155
R-squared	0.073	0.199	0.188	0.232

Table 8: Risk adjusted return and carbon emissions. The table reports the results of a linear regression between debtors (borrowers)' Scope 1, 2, and 3 carbon emissions and lenders' risk-adjusted return (ReturnPD),defined as the interest rate paied by the borrower divided by the Probability of Default (PD). **Panel A** reports results for absolute emissions. **Panel B** reports results for emission intensity of revenues defined as borrower absolute emissions divided by borrower revenues. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, creditor (lender), and NACE sector fixed-effects.

Panel A: Oil and Gas and Renewable Energy

	(1)	(2)	(3)	(4)	(5)
	IC	CURR	SOLR	EBMA	GRMA
Oil and Gas Dummy	0.217***	0.232***	0.484***	-0.394***	-0.144***
	(0.0277)	(0.0251)	(0.0240)	(0.0266)	(0.0302)
Constant	-0.0162**	-0.0166**	-0.0346***	0.0340***	0.0117
	(0.00734)	(0.00654)	(0.00625)	(0.00752)	(0.00769)
Observations	19,591	25,026	26,245	17,923	14,639
R-squared	0.032	0.013	0.055	0.082	0.211

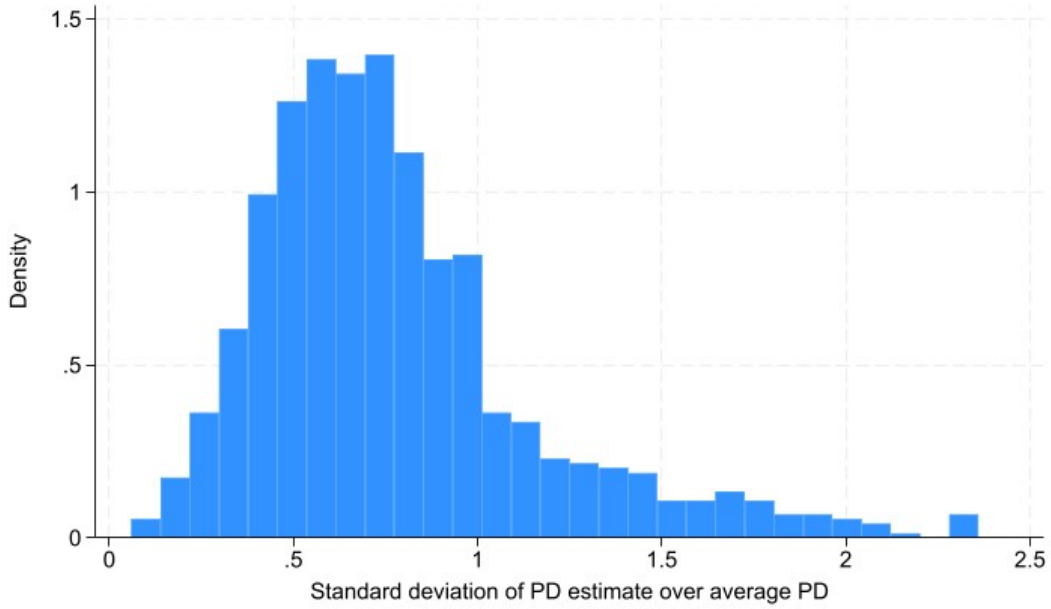
Panel B: Renewable energy and Time

	(1)	(2)	(3)	(4)	(5)
	IC	CURR	SOLR	EBMA	GRMA
Year	0.0338***	0.00382*	-0.00226	0.0356***	0.0164***
	(0.00217)	(0.00196)	(0.00186)	(0.00221)	(0.00236)
Constant	-68.15***	-7.716*	4.522	-71.69***	-33.09***
	(4.376)	(3.952)	(3.751)	(4.453)	(4.766)
Observations	18,123	23,228	24,371	16,383	13,529
R-squared	0.031	0.010	0.050	0.066	0.209

Table 9: Financial ratios - Energy sector. Panel A shows the relationship between oil and gas firms and renewable energy firms and their financial ratios. Oil and Gas dummy defined as 1 if the firm is an Oil and Gas firm and 0 if the firm is a renewable energy firm. Panel B shows the relationship between financial ratios and time for renewable energy firms. Financial ratios considered are: Interest coverage ratio (IC), current ratio defined as the ratio between Earnings Before Interest and Taxis (EBIT) and interest expenses, Solvency ratio defined as the ratio of total assets over total liabilities, EBIT margin defined as defined as EBIT over total revenues, and Gross margin defined as gross profit divided by revenue. Results controlling for time and country fixed effects. Data from 2004 to 2024. Data winsorized to the 5th and 95th percentile

Appendix

Panel A: Between creditors variation



Panel B: Between years variation

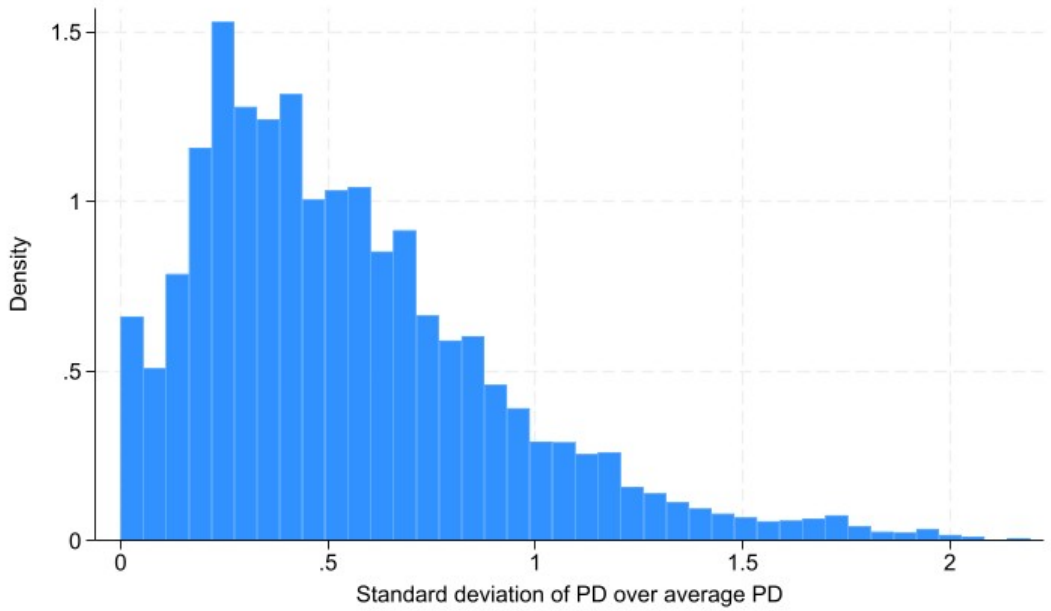


Figure A1: PD heterogeneity. Panel A shows the variation in the lenders' estimate of Probability of Default (PD) for the same borrower across lenders expressed in terms of standard deviation of PD over average PD (i.e., how different lenders' estimates differ). Sample considered only for 2022 and borrowers associated to at least 5 lenders. Panel B shows the variation in the lenders' estimate of Probability of Default (PD) for the same borrower across years expressed in terms of standard deviation of PD over average PD (i.e., how estimates vary across years).

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Cash flow to Revenue (CFOP)	-0.0101***	-0.0101***	-0.0076**	-0.0074**
	(0.0035)	(0.0036)	(0.0035)	(0.0035)
EBIT Margin (ETMA)	-0.0340***	-0.0340***	-0.0319***	-0.0322***
	(0.0040)	(0.0040)	(0.0039)	(0.0039)
Total assets (TOAS)	-0.0607***	-0.0590***	-0.0562***	-0.0550***
	(0.0030)	(0.0031)	(0.0031)	(0.0032)
Return on Assets (ROA)	-0.0191***	-0.0198***	-0.0217***	-0.0231***
	(0.0034)	(0.0034)	(0.0033)	(0.0033)
Equity to Assets (SOLR)	-0.0444***	-0.0440***	-0.0470***	-0.0465***
	(0.0034)	(0.0034)	(0.0033)	(0.0033)
Spain (ES)	0.1840***	0.1840***	0.1130***	0.1150***
	(0.0306)	(0.0306)	(0.0321)	(0.0321)
France (FR)	0.1940***	0.1940***	0.0541***	0.0545***
	(0.0060)	(0.0060)	(0.0206)	(0.0206)
Constant	-0.3780***	-0.3790***	-0.3020***	-0.3020***
	(0.0044)	(0.0044)	(0.0116)	(0.0116)
Time FE	N	Y	N	Y
Creditor FE	N	N	Y	Y
Observations	12,041	12,041	12,039	12,039
R-squared	0.1480	0.1500	0.2040	0.2060

Table A1: Probability of Default explanatory variables. The table reports the main explanatory variables of the lenders' estimates of the borrower-level Probability of Default (PD). From top to bottom: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time and creditor (lender) fixed-effects.

Panel A: Refinitiv ESG Ratings

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
E Score	-0.0731***	-0.0437	-0.101***	-0.0269
	(0.0234)	(0.0423)	(0.0247)	(0.0444)
S Score	0.0322	-0.0229	0.0684**	-0.0208
	(0.0275)	(0.0500)	(0.0285)	(0.0533)
G Score	-0.0921***	-0.0162	-0.0836***	0.00726
	(0.0202)	(0.0375)	(0.0212)	(0.0401)
Constant	-0.317***	-0.285***	-0.329***	-0.299***
	(0.0135)	(0.0247)	(0.0140)	(0.0271)
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	4,188	1,681	4,186	1,676
R-squared	0.148	0.242	0.212	0.317

Panel B: MSCI ESG rating

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
E Score	-0.000378	0.00230	0.00244	-0.00113
	(0.00176)	(0.00331)	(0.00200)	(0.00394)
S Score	-0.0181***	-0.0246***	-0.0208***	-0.0384***
	(0.00268)	(0.00481)	(0.00283)	(0.00530)
G Score	0.00355	-0.0160***	0.00283	-0.0153***
	(0.00312)	(0.00512)	(0.00332)	(0.00570)
Constant	-0.335***	-0.149***	-0.335***	-0.0846*
	(0.0252)	(0.0424)	(0.0271)	(0.0466)
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	3,360	1,329	3,358	1,326
R-squared	0.158	0.261	0.249	0.377

Table A2: Probability of Default and ESG factors. The table reports a regression between PDs and **Panel A** Refinitiv ESG ratings' Environmental, Social, Governance scores, and **Panel B** MSCI ESG ratings' Environmental, Social, Governance scores. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time and creditor (lender) fixed-effects.

	(1)	(2)	(3)	(4)
	Spread	Spread	Spread	Spread
PD	0.454***	0.308***	0.459***	0.306***
	(0.0123)	(0.0210)	(0.0124)	(0.0213)
CFOP		0.00898		-0.00665
		(0.00796)		(0.00874)
ETMA		0.0553***		0.0421***
		(0.00897)		(0.00974)
TOAS		-0.0343***		-0.0497***
		(0.00729)		(0.00779)
ROA		-0.0381***		-0.0335***
		(0.00752)		(0.00815)
SOLR		-0.00817		-0.00712
		(0.00772)		(0.00803)
Constant	-0.0101**	-0.246***	-0.00873*	-0.246***
	(0.00508)	(0.00851)	(0.00507)	(0.00853)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	42,571	11,157	42,568	11,155
R-squared	0.293	0.226	0.306	0.246

Table A3: Interest rate and Probability of Default. The table reports a regression between the interest rate charged by lenders to borrowers (spread over ris-free rate) and lenders' estimates of borrower's PDs. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (ROA), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, and creditor (lender) fixed-effects.

	(1)	(2)	(3)	(4)
	PD	PD	PD	PD
Target	-0.154***	-0.184***	-0.0876***	-0.107**
	(0.0241)	(0.0460)	(0.0254)	(0.0513)
CFOP		-0.00860		0.00258
		(0.0277)		(0.0320)
ETMA		0.0135		0.0526
		(0.0318)		(0.0347)
TOAS		-0.0733***		-0.138***
		(0.0234)		(0.0305)
TOAS		-0.117***		-0.101***
		(0.0284)		(0.0347)
SOLR		-0.0901***		-0.0611**
		(0.0248)		(0.0288)
Constant	0.00457	0.0560	-0.0349*	0.0134
	(0.0185)	(0.0351)	(0.0189)	(0.0383)
Time FE	Y	Y	Y	Y
Creditor FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	Y	N	Y
Observations	4,303	1,573	4,301	1,570
R-squared	0.074	0.231	0.144	0.222

Table A4: PD and Net zero targets. The table reports the results of a regression between a dummy variable equal 1 if the borrower has a climate target and 0 otherwise and lenders' estiamte of borrowers' Probability of Default. Control variables included: Cash flow to Revenue (CFOP), EBIT Margin (ETMA), Total assets (TOAS), Return on Assets (TOAS), Equity to Assets (SOLR), and country of debtor (borrower). Data winsorized to the 95th and 5th percentile. Sample from January 2019 to December 2023. Results controlling for time, creditor (lender), and NACE sector fixed-effects.

Panel A: Absolute Emissions - Unconditional

	(1)	(2)	(3)	(4)	(5)
	IC	CURR	SOLR	EBMA	GRMA
Scope 1 Absolute Emission	-0.0191**	-0.0498***	-0.0412***	0.00656	-0.124***
	(0.00916)	(0.00975)	(0.00888)	(0.00961)	(0.00970)
Scope 2 Absolute Emission	-0.0351***	-0.0524***	-0.000611	0.0254*	0.00252
	(0.0123)	(0.0131)	(0.0120)	(0.0130)	(0.0139)
Scope 3 Absolute Emission	-0.0512***	0.00887	0.00515	-0.0924***	0.0539***
	(0.0117)	(0.0124)	(0.0113)	(0.0124)	(0.0140)
Constant	-0.0315***	0.0930***	0.0371***	-0.0793***	0.0561***
	(0.00789)	(0.00844)	(0.00765)	(0.00847)	(0.0111)
Time FE	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y
Sector FE	N	N	N	N	N
Observations	15,153	15,970	16,170	14,501	6,951
R-squared	0.022	0.013	0.009	0.025	0.087

Panel B: Absolute emissions - Within Sector

	(1)	(2)	(3)	(4)	(5)
	IC	CURR	SOLR	EBMA	GRMA
Scope 1 Absolute Emission	0.00370	-0.0328***	-0.0123	-0.00132	-0.0785***
	(0.00980)	(0.0110)	(0.00965)	(0.0106)	(0.00978)
Scope 2 Absolute Emission	-0.0408***	-0.0800***	-0.0225*	0.0126	-0.0453***
	(0.0123)	(0.0138)	(0.0121)	(0.0134)	(0.0126)
Scope 3 Absolute Emission	-0.0183	0.00866	-0.0222*	-0.0380***	0.0318***
	(0.0116)	(0.0129)	(0.0113)	(0.0126)	(0.0123)
Constant	-0.0351***	0.0943***	0.0400***	-0.0827***	0.0633***
	(0.00735)	(0.00827)	(0.00723)	(0.00810)	(0.00921)
Time FE	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y
Observations	15,150	15,967	16,167	14,498	6,945
R-squared	0.158	0.057	0.119	0.114	0.386

Table A5: Carbon emissions and financial variables. The table shows the relationship between debtor (borrower)-level carbon emission intensity and debtor(borrower)-level financial ratios. Financial ratios considered are: Interest coverage ratio (IC), current ratio defined as the ratio between Earnings Before Interest and Taxis (EBIT) and interest expenses, Solvency ratio defined as the ratio of total assets over total liabilities, EBIT margin defined as defined as EBIT over total revenues, and Gross margin defined as gross profit divided by revenue. Results controlling for time and country fixed effects. Data from 2004 to 2024. Data winsorized to the 5th and 95th percentile

Panel A: Emission Intensity - Unconditional

	(1)	(2)	(3)	(4)	(5)
	IC	CURR	SOLR	EBMA	GRMA
Scope 1 Emission Intensity	-0.0361***	-0.0504***	-0.0301***	-0.0166*	-0.0981***
	(0.00808)	(0.00865)	(0.00785)	(0.00847)	(0.00946)
Scope 2 Emission Intensity	-0.0136	0.0560***	0.0771***	0.0846***	-0.00628
	(0.00914)	(0.00977)	(0.00887)	(0.00975)	(0.0113)
Scope 3 Emission Intensity	0.0309***	0.00703	0.00260	-0.0583***	-0.0662***
	(0.0103)	(0.0108)	(0.00980)	(0.0109)	(0.0135)
Constant	-0.0364***	0.0915***	0.0416***	-0.0873***	0.0441***
	(0.00808)	(0.00859)	(0.00777)	(0.00861)	(0.0107)
Time FE	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y
Sector FE	N	N	N	N	N
Observations	15,153	15,970	16,170	14,501	6,951
R-squared	0.014	0.010	0.013	0.025	0.086

Panel B: Emission Intensity - Within Sector

	(1)	(2)	(3)	(4)	(5)
	IC	CURR	SOLR	EBMA	GRMA
Scope 1 Emission Intensity	-0.0143	-0.0465***	-0.0165*	-0.0263***	-0.0563***
	(0.00932)	(0.0106)	(0.00928)	(0.0102)	(0.00993)
Scope 2 Emission Intensity	-0.0282***	0.0418***	0.0599***	0.0477***	-0.0118
	(0.0100)	(0.0113)	(0.00986)	(0.0111)	(0.0110)
Scope 3 Emission Intensity	0.00809	0.0570***	-0.0220*	-0.0243*	-0.0144
	(0.0125)	(0.0137)	(0.0120)	(0.0138)	(0.0142)
Constant	-0.0407***	0.0984***	0.0368***	-0.0854***	0.0412***
	(0.00760)	(0.00854)	(0.00745)	(0.00835)	(0.00891)
Time FE	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y
Observations	15,150	15,967	16,167	14,498	6,945
R-squared	0.156	0.053	0.119	0.115	0.378

Table A6: Carbon emission intensity and financial variables. The table shows the relationship between debtor (borrower)-level carbon emission intensity and debtor(borrower)-level financial ratios. Financial ratios considered are: Interest coverage ratio (IC), current ratio defined as the ratio between Earnings Before Interest and Taxis (EBIT) and interest expenses, Solvency ratio defined as the ratio of total assets over total liabilities, EBIT margin defined as defined as EBIT over total revenues, and Gross margin defined as gross profit divided by revenue. Results controlling for time and country fixed effects. Data from 2004 to 2024. Data winsorized to the 5th and 95th percentile

	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 A7: Profitability, Solvency, and Liquidity Metrics of high carbon energy and low carbon energy