Climate Risk, Green Confusion and Bank Lending

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Abstract

This paper investigates whether and how European banks incorporated climate transition risk into corporate loan pricing between 2021 and 2024. Utilizing granular data from the 2024 EBA Fit-for-55 collection, this study documents that firms with lower carbon intensity benefit from reduced borrowing costs of approximately 20-40 basis points. This ”greenium” intensified significantly after 2022 and is more pronounced for loans extended by banks with strong environmental commitments. This analysis reveals that banks employ both sectoral differentiation and within-sector ”best in class” approaches when pricing climate risk. However, this paper identifies substantial ”green confusion” in the market, as different data providers frequently disagree on firms' environmental classifications. This uncertainty undermines the effectiveness of climate risk pricing, causing banks to abandon granular within-sector approaches in favor of broader sectoral assessments. Furthermore, institutions lacking robust climate data infrastructure fail to price transition risks effectively, regardless of their stated environmental commitments.

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1 Introduction

Climate change represents one of the most profound economic transformations of our time, with significant implications for financial markets and institutions. As economies transition toward lower-carbon alternatives, financial assets might face potential revaluation based on their alignment with climate objectives and firms could see their probability of default evolve(Battiston et al., 2021; ecb, 2022). Banks, as primary intermediaries of capital allocation, play a pivotal role in this transition through their lending decisions. By incorporating climate considerations into loan pricing, banks can potentially accelerate decarbonization efforts by channeling capital toward more sustainable economic activities while simultaneously protecting their balance sheets from transition-related risks.

The pricing of climate transition risk in corporate lending represents a critical mechanism through which financial markets may facilitate—or impede—the low-carbon transition. Efficiently functioning credit markets should theoretically price all material risks, including those stemming from climate change policy, technological disruption, and shifting consumer preferences that could affect borrowers' future cash flows and creditworthiness. However, climate risks present unique challenges for financial valuation due to their long-term nature, non-linearity, uncertain timing, and potential for systemic impacts (Chenet et al., 2021). Understanding how and to what extent European banks incorporate these considerations into corporate lending decisions is therefore essential for gauging progress toward climate-aligned financial markets.

Against this backdrop, this study addresses a critical question in climate finance: How do European banks incorporate climate transition risk into corporate loan pricing? While a growing body of research examines climate risk pricing in financial markets, existing studies have primarily used as proxy for climate risk firm's carbon emissions through some specific climate data providers. This paper leverage new granular climate data from the 2024 EBA Fit-for-55 collection containing information on how European banks perceived climate intensities of their top debtors. I use this dataset to investigate whether carbon-intensive firms face higher borrowing costs, how these pricing differentials have evolved during the critical 2021-2024 period, and which types of banks most actively incorporate climate considerations into lending decisions. Furthermore, I examine the specific mechanisms through which climate risk pricing functions, the impact of measurement uncertainty on banks' pricing strategies, and the role of banks' technical capabilities in facilitating effective climate risk assessment. By addressing these questions, this paper contributes to our understanding of how financial markets are responding to climate transition challenges and the potential barriers to efficient capital reallocation during the low-carbon transition.

This study constructs a comprehensive dataset by integrating multiple European financial and climate data sources. The primary dataset comes from the European Banking Authority's "Fit-for-55" climate data collection, which required significant banks to report Scope 1 greenhouse gas (GHG) emissions for their largest counterparties, along with key financial indicators such as total revenues. The dataset allows for a granular assessment of firms' carbon intensity as perceived by European banks, defined as the ratio of absolute Scope 1 GHG emissions to total revenue. Given inconsistencies in reported values across banks due to varying data sources and estimation techniques, this study also exploits interbank differences to measure uncertainty in climate-related disclosures. To analyze the financial impact of firms' environmental performance, the dataset is matched with loan-level information from the European credit register (AnaCredit), which provides detailed records of credit relationships and agreed interest rates. By combining these datasets, the study examines how carbon intensity influences loan pricing while addressing key data challenges, such as selection bias and reporting inconsistencies.

These findings reveal a significant and growing differentiation in loan pricing based on corporate carbon intensity since 2022. Firms with lower emissions benefit from a "greenium" of approximately 20-40 basis points in borrowing costs in 2023 and 2024. Notably, this pricing differential is primarily driven by banks with strong environmental commitments, suggesting that institutional factors influence the extent to which climate risks are incorporated into lending decisions.

I further identify two key mechanisms underlying climate risk pricing: a sectoral approach, where banks charge higher rates to carbon-intensive industries, and a within-sector "best-in-class" strategy, where banks offer preferential rates to the least carbon-intensive firms within each industry. However, I find that the latter approach is often undermined by inconsistencies in environmental classification across data providers—a phenomenon termed "green confusion." As a result, many banks shift toward broader sectoral assessments, reducing the granularity of climate risk differentiation in loan pricing.

Moreover, I show that banks with weaker climate data infrastructures fail to price transition risks effectively, even when they publicly commit to sustainable finance initiatives. This underscores the crucial role of high-quality, standardized climate disclosures in enabling efficient capital allocation.

This study makes three key contributions to the emerging literature on climate finance and bank risk management: First, this study provides empirical evidence on the pricing of climate transition risks in corporate lending, distinguishing between green premium and brown penalty mechanisms. Previous studies have shown that banks are starting to price climate risk (Kacperczyk and Peydró, 2022; Mueller and Sfrappini, 2022; Boermans et al., 2024; Reghezza et al., 2022; Degryse et al., 2023) .According to this literature, there are a multitude of events that could explain or impact such a green premium: the Paris Agreement of 2015 had increase the green premium (Ho and Wong, 2023; Ehlers et al., 2022; Alessi et al., 2024), as well as the introduction of the ECB Guide on climate risk management in 2020 (Aiello, 2024), the development of state-guaranteed loans in 2020 (Buchetti et al., 2024), the first sectoral data collection and regulatory climate stress test in Europe (ACPR) (Fuchs et al., 2023), the first granular data collection and ECB bottom-up stress test in 2022, the thematic review of the ECB in 2022 analysing if banks follow the ECB Guide of climate risk management of 2022, the monetary policy tightening of 2022 (Altavilla et al., 2024) and maybe the first ECB top-down stress test of 2023 and the large-scale climate data collection Fit-for-55 of EBA in 2024 and its associated top-down stress test. This study tries not to pinpoint the impact of one event but look at the global macro dynamic of the evolution of the green premium from January 2021 to September 2024 in Europe, and find a very strong increase of the green premium in 2022-2023 and a plateau after this period.

Second, this study documents the adverse effects of climate data inconsistencies on financial decision-making, highlighting how information uncertainty weakens banks' ability to price transition risks effectively. This study quantifies the financial impacts on the credit market of "green confusion" arising from inconsistent environmental ratings. The divergence between ESG ratings is well-documented (Chatterji et al. (2016); Berg et al. (2022); Christensen et al. (2022)), and recent work suggests it may create opportunities for greenwashing (Khan et al. (2024), Hu et al. (2023)). However, the consequences for bank lending and the financement of a greener economy have received less attention (Gibson Brandon et al. (2021); Billio et al. (2021)).This paper provides novel evidence that disagreements between climate data providers lead to divergent views on borrowers' environmental profiles, hindering the efficient allocation of capital to greener firms. By demonstrating the real economic costs of inconsistent metrics, this research highlights the need for standardized climate risk reporting in the financial sector (Popescu et al., 2021; Alogoskoufis et al., 2021).

Third, this study underscores the importance of banks' technical capacity in integrating climate considerations into lending practices, revealing that mere environmental commitments are insufficient without robust data infrastructure. This climate data treatment and analysis limitations of banks also impacts banks that want to become greener/that want to foster climate change, highlighting a general problem for a better integration of climate transition risk into the pricing models of banks. ecb (2022) already identifies that a high number of European banks were not ready to deal with climate data as they had no infrastructures or process to collect, clean, store, and use climate data in their models and analysis. Some papers in the literature already discuss why climate risk transparency and data production is not enough and developing adequate system of treatment and analysis are also necessary Ameli et al. (2020).

These findings underscore the critical importance of standardized climate reporting frameworks to facilitate efficient capital allocation and enhance financial stability. Inconsistencies in corporate emissions disclosures create significant uncertainty for banks, leading to suboptimal loan pricing and potential misallocation of credit. Establishing clear, harmonized disclosure requirements—such as common methodologies for measuring and verifying Scope 1, 2, and 3 emissions—would reduce discrepancies and allow financial institutions to more effectively integrate climate risks into their decision-making processes.

These insights are particularly relevant for banking supervisors and central banks, given their mandate to ensure financial system resilience. The observed variation in climate risk pricing across banks suggests that regulatory oversight may need to be strengthened to ensure consistent incorporation of transition risks into lending practices. Supervisory stress tests incorporating climate-related risks could be expanded to evaluate banks' ability to differentiate between borrowers based on environmental performance. Moreover, integrating climate risk assessments into prudential regulations—such as capital requirements—could incentivize banks to refine their methodologies for measuring climate exposures.

Additionally, the findings highlight the need for clear guidelines on how banks should assess and manage both physical and transition risks in their loan portfolios. While large corporations benefit from well-developed sustainability reporting mechanisms, smaller firms often lack the resources to provide comprehensive emissions disclosures. Policymakers could consider targeted measures—such as technical assistance programs or green investment incentives—to help smaller firms transition to low-carbon operations without facing excessive financing costs.

The paper proceeds as follows. Section 2 describes the data and presents summary statistics. Section 3 describes our empirical strategy and analyses do banks price climate risk, reproducing the results obtained in the literature. Section 4 investigates how banks perform the pricing of climate transition risk, section 5 investigates the impact of green confusion and banks' climate capabilities. I draw conclusions in Section 6.

2 Data and descriptive statistics

To investigate the research questions, I construct a comprehensive database by compiling the data from the climate data collection from banks organised by EBA "Fit-for-55", the European credit register Anacredit, credit ratings from all agencies reported in Centralised Securities Database (CSDB), and banks' financial and regulatory statements from FINREP and COREP.

Granular European climate data collection Fir-for-55

The primary component comes from the European Banking Authority' climate data collection announced in July 2023 and conducted from December 2023 to March 2024, based on data at end-2022. The climate data collection organised in 2024 was performed in the context of a top-down climate scenario analysis. On 8th March 2023, European Commission asked the European Banking Authority (EBA), ECB, ESRB and European Supervisory Authorities to perform a climate risk scenario analysis exercise. The primary focus is to assess the resilience of the financial sector in line with the Fit-for-55 package of the European Commission, while gaining gaining insights into the capacity of the financial system to support the transition to a lower carbon economy even under conditions of stress. Templates and template guidances of this data collection are publicly available on the websites of the EBA ("One-off Fit-for-55 climate risk scenario analysis").

In this collection, significant European banks had to report greenhouse gas (GHG) emissions data for their largest counterparties, including Scope 1, 2, and 3 emissions, along with net zero reduction targets for each counterparty (defined as the expected reduction in the absolute amount of Scope 1 and 2 emissions, expressed in percentage until 2030). Absolute S1 GHG emissions were defined as the total amount of direct greenhouse gas emissions that are emitted from sources that are controlled or owned by an organisation over one year (e.g., emissions produced by manufacturing processes, burning diesel fuel in trucks, fugitive emissions such as methane emissions from coal mines, or production of electricity by burning coal). Banks also had to report the total assets, total revenues, total operating expenses and total debt of each of their counterparties.

Each participating bank had to report data for their top 15 counterparties, in terms of exposure value (or in terms of total bonds and equities fair value for market risk), for each climate-relevant NACE sector, for both credit risk and market risk exposures. Knowing that there was in total 22 groups of NACE 2 sectors covered by this data collection, this results in a maximum of 660 counterparties reported per bank. Banks had to obtain the information regarding their counterparties (also called debtors or firms in the paper) following guidelines edicted by the EBA: first, banks had to try obtaining this information through climate data providers or by asking their counterparties directly (e.g., company sustainability report). In case a banks used multiple climate data providers, they had to define an order of priority between them to fill their templates. If a counterparty was not present in any climate data provider database a bank had access too and the counterparty haven't publicly communicated on its climate impact, banks had to obtain it leveraging on estimation techniques and proxies. Banks had to fill an explanatory note template as they had to explain how they filled the templates: banks had to present their priority ranking between the different ways to obtain climate-related data, and thus identicate all climate data providers they used to access the data as well as the priority they give to each one. They also have to present precisely the estimation methods employed when no actual data was available.

The counterparties' countries covered by the climate data collection Fit-for-55 are both EU and non-EU countries. The counterparty NACE sector allocation shall be based on the nature of the immediate counterparty and not the consolidated counterparty's group. This non consolidation on the counterparties' side simplifies a lot our study as it is possible to use directly the Legal Entity Identifier and RIAD code (Register of Institutions and Affiliates Database code) to map these entities to other databases. Banks should map their corporate counterparty to one single sector based on its principle activity, i.e. the activity that generates the highest share of the counterparty's revenue. When institutions' counterparty is a holding company (parent name in the templates), institutions shall consider the NACE sector of the specific obligor under the holding company (if different than the holding company itself) which receives the funding (i.e., the specific subsidiary of the holding company in question) rather than that of the holding company; particularly in those cases where the obligor that is benefiting from the financing is a non-financial corporate. Similarly, when the direct counterparty of the institution (the obligor) is a special purpose vehicle (SPV), institution shall disclose the relevant information under the NACE sector associated with the economic activity of the parent company of the SPV.

The French banks participating to these climate data collection is highly representative of the entire French banking sector: they represent 85% of total assets (around 7900 billions out of 9289 billions euros at the end of 2022, which is the reporting date of Fit-for-55). The French banking sector is mainly oriented towards loans rather than market operations: loans represented 65% of French banks' total assets in 2023. Total assets of the banking sector represented 320% of French' GDP. Yet, the business models of these banks are highly diversified and heterogeneous: among the eleven French banks that participated in the climate data collections (including Bank of America Securities Europe SA in 2024), their business models can be categorized as follows: six operate as universal banks (BNP Paribas, BPCE, Crédit Agricole, Crédit Mutuel, HSBC Continental Europe, and Société Générale), three focus on specific segments (La Banque Postale primarily on retail, RCI on automotive financing, and Bank of America Securities Europe SA on investment banking), and two are public development banks (Bpifrance and SFIL). Regarding their climate commitments as of 2024, these banks show varying levels of engagement: five banks (BNP Paribas, La Banque Postale, Crédit Agricole, Société Générale and HSBC Continental Europe) are members of the Science Based Targets Initiative (SBTi), while six banks (BNP Paribas, BPCE, La Banque Postale, Crédit Agricole, HSBC Continental Europe, and Société Générale) have joined the Net Zero Banking Alliance (NZBA). All these banks are directly supervised by the ECB's Single Supervisory Mechanism.

The main two variables I use from this database is the Scope 1 greenhouse gas emissions of each firm (”Absolute S1 GHG emissions” in Fit-for-55 data collection) reported by banks as well as their total revenues (”Total revenues” in Fit-for-55 data collection). These two variables are used to constitute a third variable called ”Carbon intensity” which is the ratio between the Scope 1 greenhouse gas emissions of a debtor and the debtor's total revenue, following the formula proposed by ECB for the Analytical indicators on carbon emissions (greenhouse gas emissions of a debtor/issuer divided by the debtor's/issuer's total revenue). Absolute Scope 1 greenhouse gas emissions (tCO2e) are defined as the total amount of direct greenhouse gas emissions that are emitted from sources that are controlled or owned by an organisation over a specific period (e.g., emissions produced by manufacturing processes, burning diesel fuel in trucks, fugitive emissions such as methane emissions from coal mines, or production of electricity by burning coal). It is reported by each bank for each of their largest counterparties at the end of 2022. Total revenues are defined as the figure reported by the obligor in the Income Statement (in € million). All variables are defined in Section A.1.

In the parent, firms are often divided into two groups, the ”green” and ”brown” firms, depending on their carbon intensity. The firms with a carbon intensity higher than the median are considered ”brown” and the firms with a carbon intensity lower than the median are considered ”green”. This distinction is done to make comparison easier. There is two exception to this classification: in Figure 10a, firms will however be decomposed into three groups with the addition of the ”reference group”, composed by the firms with a carbon intensity between the percentile 33 and 66. In Figure 10b, firms will be decomposed into five groups (very green, green, reference group, brown and very brown), each representing 20% of the total sample and each groups corresponding to a level of carbon intensity still defined based on the percentiles of the distribution.

All European systemically important institutions had to participate to these data collection. A total, 110 consolidated banking groups participated in the 2024 data collection. The data had to be provided at the highest level of consolidation of the banking groups. The scope of the banking consolidation is the perimeter of the banking group as defined by the CRR/CRD. However, as I only have access to the data collection for French banks, this study concentrates on this sample. Eleven french banks had to participate to the climate data collection, the complete list and their associated Legal Entity Identifiers is described in Table 1. Two choices were possible based on that data access limitation: only analyse bank-firm relationships for banks reporting their own counterparties, which would result in a small sample which could bias the estimations as the date fixed effects and even firm fixed effects could not be representative as other loans given to the counterparties by banks that do not report them would not be included (because they are not on the sample of French reporting banks). The other approach would be to consider all loans given by all banks (even if they are not on the sample of French reporting banks), but in this case I need to fix the fact that I do not observe carbon intensity reported by all banks as they do not all participate to the Fit-for-55 climate data collection. The solution I find is to apply to each firm the average value of all banks that report it.

A distinctive feature of our dataset is its ability to capture the divergence in banks' assessment of firm-level environmental performance. The methodological notes reveal substantial heterogeneity in how banks prioritize different data providers and handle missing information. This variation results in situations where the same firm may be classified as green by one bank and brown by another, reflecting the current state of "greenness confusion" in the market. Banks employ different methods for imputing missing emissions data and establish varying hierarchies among data providers, leading to inconsistent environmental assessments across institutions. The methodological notes reveal that each banking group rely on multiple external climate data providers for GHG emissions information. Our analysis shows that banks subscribe to an average of four climate data providers from a pool of 12 unique providers used across the banking sector. This multiplicity of data sources creates notable variation in how banks assess the environmental performance of identical firms.The reliance on self-reported carbon intensity data may introduce measurement errors or biases, but it is also a positive point of the paper. In section Section 5.1 I use the heterogeneity of reported values across reporting banks for the same entities to measure the uncertainty it exists about the real carbon intensity of some firms.

As the data was reported by banks themselves in a short amount of time through a ad-hoc data collection, and even if there were two quality assurance cycles, some errors, absurd values and/or misfilling could still be present in our final data. Also, sometimes banks decided to report the carbon intensity of the ultimate parent company / the firm' consolidated group instead of precisely the entity they lend to. In order to remove these values that might bias our estimation, I apply two filters: first, I removed all reportings with a carbon intensity superior to 100 000 tCO_2/millions euros and inferior to zero (absurd values). Second, I remove all reportings for which the difference of intensity reported by the differents banks (intensity reported by a bank for an entity divided by the median of all intensities reported by all banks for the same entity) is superior to 66 (percentile 99). In case of a difference higher than this threshold, it is considered that the entity that banks analysed cannot be the same, thus it is removed to reduce risks that may bias the results. This filter was added to cover the second problem identified, as sometimes banks may report the intensity of the parent company if they cannot find any relevant information about the subsidiary company, in line with the rules of the template guidance. Note that there is no temporal dimension in the Fit-for-55 climate data collection, as banks have to report only climate information about their main debtors at observed in the end of 2022. This could be a limitation as it is not possible to perform a panel study useful to control for unobserved differences between green and brown firms. Alternative econometric approach taking into account this limitation is proposed in Section 3.3.

The data presents several important limitations that warrant discussion. First, the ECB climate data collection covers only the largest counterparties per NACE code, potentially introducing selection bias in our sample of reported firms. Second, the reliance on multiple data providers with varying methodologies creates challenges in standardizing environmental performance measures across banks.

Banking relationships characteristics from the Euro Area Credit Register

The key variable of interest is the annualised agreed rate in accordance with Regulation (EU) No 1072/2013 of the European Central Bank (ECB/2013/34): interest rate that is individually agreed between the reporting agent and the non-financial corporation for a loan, converted to an annual basis and quoted in percentages per annum. The AAR covers all interest payments on loans, but no other charges that may apply.

To obtain the interest rates of each loan given by each bank to each firm in my sample, I match the climate data from the data collection Fit-for-55 with granular loan-level information from the European credit register (AnaCredit), which provides confidential detailed information on credit relationships between banks and firms. Only fixed interest loans are considered for this study as variable rate report only the interest rate spread over a reference rate, but the reference rate is poorly indicated in Anacredit, biasing the comparison between firms. The level of analysis is the credit relationship (bank - firm - date level), thus thbe variable of interest is more precisely the weighted average interest rate, with the weights corresponding to the total outstanding nominal amount of each loan between a creditor and a debtor, for a given date. Only standard term loans (instrument "1004" in Anacredit) were considered to avoid mixing loans of very different natures, and finally only the majority of loans with a positive interest rate were kept in order to avoid capturing exotic loans or outliers values that might bias our analysis.

The Fit-for-55 climate data collection required banks to report greenhouse gas (GHG) emissions of their primary counterparties as of end-2022. Our study period from January 2021 to September 2024 encompasses approximately two years before and after this reference date. This timeframe was deliberately chosen to minimize the risk of using outdated climate data, as our dataset lacks a temporal dimension. We reasonably assume that firms' carbon intensity remained relatively stable during this four-year window, given that meaningful climate transitions typically occur over longer horizons.

In the export done, all credit relationships between non-financial corporations and banks are considered if they represent a total carrying amount of at least 500.000€. While the scope of this template is exposures to non-financial corporations, both SME and non-SME, they are however very few SME in the database as the data collection only cover the top 15 non-financial issuers for each group of climate-relevant NACE sector. This choice was done to reduce the size of the database and faciliate the export.

Our unit of observation to test bank lending behavior is the credit relationship level, between a creditor (a bank, S122 in ESA 2010) and a debtor (a non-financial corporation, S11 in ESA 2010), observed at the monthly frequency. As the submission to the data collections should be provided at the highest level of consolidation of the banking groups and that Anacredit is a reporting at the individual level, banking groups are reconstructed in Anacredit based on the Register of Institutions and Affiliates Database (RIAD) from ECB and the template COREP C06 where banks have to to report all their branches, affiliates and subsidiaries. The head of a banking group is identified as the entity of a banking group with the highest total assets, which corresponds when applicable to the entity reporting to the EBA's transparency exercise for example. As banks had to fill the data collections regarding only entities they directly lend to and not the whole business groups, debtors in Anacredit are not consolidated. However, RIAD database is used to merge the firms identified in the data collections with a diversity of identifier code types (such as SIREN (national French corporate ID), ISIN or LEI) to Anacredit, where firms are mainly identified through a RIAD identifier. 80.7% of the firms reported in the data collections have been found in Anacredit by using the reported RIADs and/or LEIs (1139 firms identified out of 1412 firms reported in the granular credit template of the climate data collection).

Financial and regulatory reportings Finrep and Corep

Finally, financial and regulatory variables at the bank-time level come from FINREP and COREP reporting frameworks, providing standardized data on bank balance sheets, income statements, and regulatory capital positions. The variables coming from these reportings are presented in Section A.1 and they are use as control variables in the econometric regressions to limit the bias of omitted variables, as interest rates offered by banks could be directly impacted by their profitability, solvency, size, ratio of non-performing loans and provisions.

Descriptive statistics

Our final sample of the study used for the econometric analysis encompasses 667 unique banking groups (containing 63 banking groups out of the 110 participating to the Fit-for-55 climate data collection) and 1139 borrowing firms. It is obtained after removing all rows with missing values on critical variables and applying all the filters listed above is presented in Annex.

Figure 1 presents the total outstanding normal amount of all loans covered in the sample, which rates from 90 to 115 billions euros. Knowing that there is 1139 companies in the final sample, that means that in average a firm in the sample has a total amount of banking loans equals to around 100 millions euros at a given date in our study period.Table 3 indicates that the average credit relationship amount is 8.9 million euros, with the first quartile being 2.7 millions and the third 31.7 millions.

Table 1 brings information, about what is the countries of the creditors and debtors present in the final sample. Because of the construction process of the database, linked to the fact that only the Fit-for-55 granular reportings of French banks were available for this study, the majority of creditors (35%, in share of total outstanding amount) and debtors (33%) are from France. The other debtors come from Germany (12%) , Italy (12%) , United States (9%) and Netherland (4%) . Banks are mainly located after France in Germany (18%), Italy (11%), Netherland (10%) and Spain (9%). The sample is pretty diversified composed, with banks and firms from a diversity of countries, bothn european and non-europeans countries regarding debtors.

Table 3 presents complete descriptive statistics for the final sample after applying all the filters listed above. Regarding the dependent variable, the weighted average interest rate of loans given by a bank to a firm at a certain date, this variable averages to 2.40% (median of 1.61%), with a standard deviation of 1.94%, ranging from 6 basis points for firms in the lowest decile to 5.34% for those in the top decile. Figure 4 illustrates the evolution of interest rates over time, comparing the sample used in this study with broader corporate loan market data from MIR statistics for the Euro Area and the ECB's main refinancing operations rate. The serie used from MIR is MIR.M.U2.B.A20.A.R.A.2240.EUR.O, which is the monthly average interest rate observed in Euro area (changing composition) for loans offered by deposit-taking corporations except the central bank (S.122) to non-Financial corporations (S.11), covering all outstanding amount (not only new loans) and all maturity, and labeled in euro. From early 2021 to mid-2022, interest rates remained relatively stable, with both the study sample and the Euro Area MIR statistics fluctuating around 1–2%, while the ECB's main refinancing rate stayed at 0%. However, starting in mid-2022, all rates exhibit a pronounced upward trend, coinciding with the ECB's monetary tightening cycle. By early 2023, the ECB's refinancing rate surged beyond 3%, with corporate loan rates following suit. At their peak, interest rates in the sample and the Euro Area MIR statistics reach approximately 4%, before exhibiting a slight decline in early 2024. The sample of the study closely tracks the MIR statistics, while being slightly lower of around 20 basis points.

The slight discrepancy of about 20 basis points between the study sample (composed of mostly big corporations as they are in the top 20 of a NACE sector for at least one French banking group) and the broader Euro Area MIR statistics could be explained by several factors, such as credit risk premium: larger corporations often have lower credit risk than smaller firms, as they are more likely to have stable revenue streams, better financial health, and access to diverse funding sources. As a result, they might secure loans at slightly lower interest rates compared to the broader corporate market. The MIR statistics capture a wide range of corporations, including those with higher risk profiles, which could push the overall rate slightly higher. Big corporations also typically have greater bargaining power due to their size, financial stability, and reputation. This power enables them to negotiate more favorable terms with lenders, including slightly lower interest rates compared to the broader market, which might include smaller or riskier borrowers. Large corporations may have access to more favorable funding options, such as bond markets or private placements, which could offer better terms than typical corporate loans. This access to alternative funding sources might help lower their borrowing costs relative to the broader corporate loan market, reflected in the slightly lower rates.

3 Do Banks Price Climate Risk?

In this section, I use the data described in Section 3 2 to first reproduce the analysis conducted in other research papers. I address two fundamental questions: First, do banks incorporate climate risk into their lending rates? Second, do committed banks assign a higher price to climate risk? These analyses will establish the foundation for the more advanced investigations presented in the subsequent section.

3.1 Descriptive statistics

I begin by providing descriptive evidence on banks' pricing of climate risk through a visualization of interest rates charged by banks in my sample to firms with varying carbon footprints between January 2021 and September 2024. Figure 5 presents a comparison of monthly average interest rates charged by banks in my sample to counterparties reported by at least one French bank in the Fit-for-55 climate data collection. In the left panel, I compare average interest rates between firms in the top 50% percentile by carbon intensity (brown firms/ high-emissions firms) and those in the bottom 50% percentile (green firms/low-emission firms). The right panel employs a more restrictive definition, focusing exclusively on the extremes by comparing only the top 25% highest-emitting firms with the bottom 25% lowest-emitting firms.

Both panels reveal two consistent patterns: First, before 2022, firms with higher carbon emissions intensity paid, on average, the same interest rates compared to firms with lower carbon emissions intensity. There appears to be either no green premium or a very minimal one of approximately 5 basis points according to the right panel (with the restrictive approach). We observe in aggregated statistics that prior to 2022, interest rates for both green and brown firms remained relatively stable and comparable, hovering around 1.37%. Second, beginning in 2022, firms with higher carbon emissions intensity began facing systematically higher borrowing costs. This pattern intensifies over time, particularly when comparing the top 25% to the bottom 25% (right panel). By 2024, the interest rate gap between high and low carbon-intensity firms reached approximately 31 basis points in the broad classification (left panel) before decreasing to 16 basis points at the end of the study period. In the restricted classification (right panel), this gap widened to approximately 52 to 70 basis points in 2024. The temporal pattern is particularly noteworthy as a clear divergence emerges in 2022 and 2023. According to the literature on green premium, multiple factors could explain this trend: In 2021, ACPR organized the first sectoral data collection and regulatory climate stress test for French banks (Fuchs et al., 2023). In 2022, the ECB conducted its first granular data collection and bottom-up stress test, as well as a thematic review analyzing how effectively banks were incorporating climate considerations and whether they adhered to the 2020 ECB guide on climate risk management (Aiello, 2024). Furthermore, the 2022 monetary policy tightening forced banks for the first time to restrict their credit supply, necessitating choices about which debtors to continue financing rather than supplying the entire market, and at which prices. This selective lending approach could affect the pricing of climate risk according to Altavilla et al. (2024). Finally, in 2023, the ECB conducted its first top-down stress test, and the Fit-for-55 climate data collection commenced.

Examining the dynamic in the descriptive statistics suggests that the observed effect likely results from a combination of multiple factors, as the trend increases progressively throughout the entire period rather than exhibiting a single discrete jump. The steeper increase in borrowing costs for carbon-intensive firms after 2022 may reflect banks' growing incorporation of climate considerations into their credit risk assessment frameworks, potentially in anticipation of stricter banking climate regulation and climate-related disclosure requirements. My objective in this paper is not to determine which factor might be most significant in explaining this dynamic; therefore, I will leave this avenue for further research.

Summary of Hypotheses: Explain what you expect and why (e.g., ”We expect banks to charge higher spreads for firms with higher carbon intensity due to reputational and regulatory risks.”).

3.2 Cross-section OLS

While this preliminary evidence suggests that euro-area banks do price climate risk, it may be vitiated by composition effects, as firms with different carbon footprints may differ in many other respects, such as credit risk, size, location, etc. To take these important concerns into account, in what follows I provide evidence based on a cross-section OLS estimation as I do not observe carbon intensities in a time dependent way. To investigate whether banks price climate risk in their lending rates, in Table xxx I estimate variants of the following specification:

$$\begin{aligned}\text{Interest rate}_{b,f,t} =& \beta_1 \text{carbon intensity (log STD)}_f \\ &+ \beta_2 \text{probability of default (log)}_{b,f,t} \\ &+ \beta_3 \text{maturity (log)}_{b,f,t} \\ &+ \beta_4 \text{non performing status}_{b,f,t} \\ &+ \beta_5 \text{impairment ratio}_{b,ft} \\ &+ \beta_6 \text{protection ratio}_{b,f,t} \\ &+ \beta_7 \text{outstanding amount (log)}_{b,f,t} \\ &+ \theta_{f,t} + \theta_{b,t} + \theta_{b,f,t} \\ &+ \alpha_t + \alpha_b + \alpha_f + \epsilon_{b,f,t}\end{aligned} \tag{1}$$

Where Interest $\text{rate}_{b,f,t}$ is the weighted average interest rate charged by bank b on its loans to firm f in month t (expressed in percentages per annum). The coefficient b_1 captures average carbon risk premia of banks during the whole study period 2021-2024. The carbon intensity is the ratio between the Scope 1 greenhouse gas emissions of a debtor and the debtor’s total revenue. It is put into logarithm then standardised (I substract the average value and divide by the standard deviation of the variable) in order to facilitate the interpretation of the coefficient as it might be difficult to comprehent the scale of carbon intensity (ton of CO2 equivalent emitted divided for one million of total revenues). The coefficient b_2 captures the credit risk of the counterparty estimated by bank b, or by the average of the others banks if bank b does not use the internal rating-based approach). β_4 to β_7 control for the fact that different loan maturity, non performing status, impairment ratio, protection ratio and outstanding amount of loans could very directly influence the interest rate proposed by banks. The regressions are saturated with a diversity of control variables at the bank-date and firm-date levels ($\theta_{b,t}$ + $\theta_{f,t}$: the CET1, ratio of non-performing loans, provisions ratio and return-on-assets ratio of banks, as well as the annual turnover and total assets (in log) of firms) as well as fixed effects: time FE α_t, banks FE α_b, firm sector NACE 2 α_{f_sector} as well as in some specifications bank-firm, bank-date and firm sector-date. Finally $\epsilon_{b,f,t}$ is an error term. I do not include firm fixed effects for now as I do not observe in the time dimension the carbon intensity of firms, thus integrating them would absorb β_1 and thus prevent the identification of the coefficient of interest. I however consider a specification with industry-location-size (ILS) fixed effects, which compare firms with different carbon emission intensities within the same industrial sector, country and size class as in Degryse et al. (2019). Standard errors are clustered at bank-month level.

Simplify the output explanation: A 1-standard deviation increase in carbon intensity is associated with a 20 basis point increase in loan spreads, significant at the 1

Table 6 presents the results of our cross-sectional OLS estimations investigating whether banks price climate risk in their corporate lending rates. Across all specifications, we observe a positive and statistically significant relationship between our descriptive evidence. In the baseline specification (column 1), which includes only bank and time fixed effects, a one standard deviation increase in carbon intensity is associated with a 3.8 basis point increase in interest rates, significant at the 10% level. When adding firm sector fixed effects in column (2), the coefficient more than doubles to 8.1 basis points and becomes significant at the 1% level. This suggests that comparing firms within the same sector reveals a stronger climate risk premium, as cross-sector differences may otherwise obscure this relationship.The coefficient remains stable across more saturated specifications, ranging from 8.1 to 9.6 basis points. This stability persists even when controlling for bank-sector fixed effects (column 4), sector-time fixed effects (column 5), and bank-time fixed effects (column 6), which absorb any time-varying bank or sector-specific factors. The consistency of the carbon intensity coefficient suggests a robust relationship that is not driven by unobserved heterogeneity at these levels.

The coefficient is not only statistically significant but also economically significant: the difference of interest rate between a very brown and very green companies (two standards deviation of differences on the carbon intensity of the counterparties) could be up to 18 basis points. To place these estimates in perspective, recall that in our sample the median interest rate in the sample is 160 basis points and notice that the magnitude of the implied climate premia is equivalent to a 1% increase of probability of default.

Regarding the control variables, other firm and loan characteristics also demonstrate predictable relationships with interest rates. A higher probability of default loan have a significant and positive impact on the interest rates of corporate loans. The maturity also consistently shows a positive and significant relationship with interest rates, indicating that longer maturity is associated with higher interest rates, reflecting the term premium typically observed in financial markets. The protection ratio also displays a positive and significant association in most specifications, indicating that banks charge higher rates for loans with greater collateralization, potentially reflecting higher risk assessment for these loans. Interestingly, non-performing loan status and outstanding loan amount do not show significant relationships with interest rates across specifications. The impairment ratio is only marginally significant in column (2), suggesting these factors may be secondary in banks' pricing decisions compared to carbon intensity, probability of default, and maturity. The explanatory power of these models is substantial, with R-squared values ranging from 0.49 in the baseline specification to 0.71 in the most saturated model (column 4). This indicates that our set of variables and fixed effects captures a significant portion of the variation in interest rates charged by banks.

Overall, these results provide robust evidence that banks incorporate climate risk into their lending rates, with carbon-intensive firms facing higher borrowing costs even after controlling for traditional risk factors and various fixed effects. The magnitude of this climate risk premium is economically significant and comparable to that of traditional credit risk factors, suggesting that banks view climate risk as a material consideration in their lending decisions.

This estimation could however lack external validity and don't apply to the integrality of the corporate lending portfolio of banks. This sample is constituted mainly of large companies representing an important share of the credit portfolio of reporting banks: only the top 15 couterparties per NACE sector are reported by the French banks in their climate data collection Fit-for-55. It could makes sense that banks are particularly attentive to the climate risk of their top counterparties as these are the entities that have the most weights on their climate reportings and could impact the most their reputation. It is possible that the pricing of climate risk is lower for small companies, and this is something I cannot test given the dataset I have, composed only of firms that represent an important share of the credit portfolio of banks.

3.3 Dynamic analysis

This cross-section OLS analysis is a first step and is robust to a serie of different specifications but is subject one limit: green firms can be different from brown firms in an unobserved way that I cannot control with the available data. Ideally I would like to control for unobserved heterogeneity in firms by interating a firm fixed effects, but if I do that I will not be able to estimate the coefficient of interest which does not have a time dimension. A solution to that is to analyse the impact of carbon intensity dynamically through time, by interacting carbon intensity with a date fixed effects with January 2021 as the reference date. That way we cannot estimate the impact of being a polluting firm but we gain the possibility to analyse how the impact of being a polluting firm evolved through time while controlling for all the unobserved heterogeneity in firm with a firm fixed effects. I estimate this model with the following specification:

$$
\begin{aligned}
\text{Interest rate}_{b,f,t} = & \beta_1 \text{carbon intensity (log STD)}_f \\
& + \beta_2 \text{carbon intensity (log STD)}_f \times \alpha_t \\
& + \theta_{b,t} + \theta_{f,t} + \theta_{b,f,t} \\
& + \alpha_t + \alpha_b + \alpha_f + \epsilon_{b,f,t}
\end{aligned} \tag{2}
$$

With α_t a set of monthly time fixed effects and all the other elements being the same as in equation 1. In this specification, β_1 cannot be estimated and the coefficient of interest becomes β_2.

The results of this dynamic analysis are presented in Figures 7 through 11 and Table 1. Table 1 provides the detailed regression results for the dynamic models that corresponds to the images presented just before. To improve readability, the set of date fixed effects was replaced by a set of year fixed effects, 2021 being the reference year. This enables us to drastically reduce the number of fixed effects, going from 45 to 4. The names of the specifications are the same between table 5 and charts xxx.

Figure 7 illustrates the dynamic pricing of climate risk in corporate loans by banks, showing the estimation of the coefficients β_2 across different specifications. The figures reveal a consistent pattern: First, In the initial period spanning from early 2021 to mid-2022, we observe that the coefficients fluctuate around zero, with zero always being included in the confidence intervals, indicating no significant increase of difference in loan pricing between high and low carbon-intensive firms during this period, comparatively to January 2021 (the interpretation of the results here should always be done with respect to January 2021 as we cannot estimate β_1 due to the introduction of firm fixed effects).

However, a notable shift occurs in mid-2022, with the coefficients beginning to trend upward and becoming increasingly positive. By early 2023, the coefficients become statistically significant across all specifications, as evidenced by confidence intervals that no longer contain zero. This transition suggests that banks had systematically charge higher interest rates to carbon-intensive firms relative to cleaner firms during this period, compared to january 2021, reflecting a growing awareness of the financial implications of climate change- or regulatory constraints associated to climate risk management. Finally, in all specifications, the elasticity between carbon intensity of firms and loan interest rates applied by banks to their counterparties seems to stabilise during 2023, with the coefficient β_2 staying stable or slightly decreasing during 2023 and 2024 depending on the specifications.

This result confirms the dynamic of increasing pricing of climate risk identified in descriptive statistics presented in section 1, even after controlling for a lot of observed heterogeneity between banks and firms with controls variables and even unobserved heterogeneity by saturating the regressions with fixed effects, even firm fixed effects.

The magnitude of this effect is economically significant. Based on the regression results in Table 1, the interaction term between carbon intensity and the year 2023 shows a coefficient of approximately 0.14 (columns 1-4), indicating that a one standard deviation increase in log carbon intensity is associated with an additional 14 basis points in interest rates during 2023 compared to the reference period of January 2021. The effect remains similar for 2024, with coefficients ranging from 0.085 to 0.155 across specifications. Specifications 2 through 5 progressively introduce additional controls and fixed effects to ensure robustness. Specification 2 adds loan-specific controls including probability of default, maturity, non-performing status, impairment ratio, protection ratio, and outstanding amount. Specification 3 further incorporates bank and firm controls. Specifications 4 and 5 add bank-firm fixed effects and bank-time fixed effects, respectively, to capture potential relationship-specific pricing factors and time-varying bank characteristics.

The consistency of the pattern across all specifications strengthens our findings. Even in the most demanding specification (column 5), which includes bank-time fixed effects to control for time-varying bank characteristics, the coefficients for 2023 and 2024 remain positive and statistically significant at the 1% and 5% levels, respectively.

While our focus is on the pricing of climate risk, in Table A5 of the Appendix we check what happens if the dependent variable in the panel regressions is the credit relationship volume of loans, and no significant impact can be identified across all specifications. A negative effect appears around mi-2022 of about -2% for 1 standard deviation of carbon intensity and it stays stable afterward, but this effect is not significant in any of the specification that was tested.

Matching approach

To improve causal inference in econometric estimation and helps mitigate selection bias by ensuring that the groups of green and brown firms are comparable in terms of observable characteristics, I apply as a robustness check a matching algorithm between green and brown firms.

We could imagine that in our study, being a green firm is a a non-random condition as each firm decide how it want to produce and what level of greeness they want to achieve. This choice could lead to confounding factors that may bias the estimation of treatment effects. Matching techniques, such as nearest neighbor matching, create a control group that closely resembles the treated group based on covariates, reducing the risk that differences in outcomes are driven by pre-existing characteristics rather than the treatment itself.

To reduce these concerns, I apply a matching algorithm on debtors which is a combination of exact matching on the activity sector NACE 2, the institutional sector ESA and the country of the debtor, as well as a mahalanobis distance minimisation (closest neighbors) on two main variables: the probability of default and the size, computed as the logarithm of the total outstanding amount of a debtor. The minimisation of mahalanobis distance is done only within firms of the same activity sector, institutional sector and country. For each green firm, I select the brown firm with the lowest matching score, representing the closest match in terms of default risk and size within the same country, sector, and industry. It is a selection with replacement, so multiple green firms can be matched with the same brown firm. To account for cases where a brown firm might be matched to multiple green firms, I implement a weighting system. Each brown firm receives a weight equal to the number of green firms it matches with.

Annex xxx presents the complete methodology procedure and tables xxx presents the results of the econometric regressions estimating the pricing of climate risk by banks in their corporate loans. This table reproduce completely table xxx but with the matched sample and same thing for charts xxx that reproduce charts xxx.

As we can observe in table xxx and chart xxx, the results have the same significativity and same sign as with the estimation on the unmatched sample. The magnitude of the coefficient b2 is however slightly smaller than with the unmatched sample in most specifications, going from 13 basis points in specification 3 with the unmatched sample in 2024 to 12,4 basis points (from 8.5 bps to 9.3 bps in specification 5 however). The only difference in significance is that the coefficient beta in 2024 is not significant anymore in specification 4 with the matched sample, specification 5 being the one saturated with firm x bank + date fixed effects. The coefficient is however still significant at the 5% confidence interval for the year 2023.

This methodology has however the disadvantage of reduction the size of the sample, as for some green firms it is not possible to find a brown firm within the same country and the same activity and institutional sectors given our original sample. In our case, this leads the total sample size to go from 131,653 observations to 77,670 observations, reducicng the sample size by -41%. For this reason, the matching methodology is only use as a robustness check and not as the baseline approach for the rest of the study.

4 How banks perform the pricing of climate transition risk?

In this section, we try to go further by analysing how banks implement their differenciated pricing on climate transition risk. First, I analyse the non-linearity of climate risk pricing in order to identify if banks apply a green premium or a brown penalty, or both. Second, I analyse which banks perform this climate transition risk pricing, in order to identify a potential "When green meets green" effect as theoretize by Degryse et al. (2023). Third, I analyse what counts the most for banks between backward-looking indicators (such a the carbon intensity) or forward-looking indicators, (such as debtors' target of carbon emissions reduction). Finally, I analyse what is the level of analyse of banks, which can be a sectoral approach, favorizing green sectors of activity, or within sectoral (best of the class approach) by favorizing the greenest debtors in the brown sectors.

4.1 Green premium or brown penalty? Analysis of the non-linearity of climate risk pricing

While our previous analyses have explored the dynamic evolution of climate risk pricing, they implicitly assumed a linear relationship between carbon intensity and loan pricing. However, the relationship between climate risk and financial pricing may exhibit non-linearities, with potentially different effects across the carbon intensity spectrum. To investigate this possibility, I decompose firms into multiple carbon intensity buckets and analyze their respective pricing dynamics.

$$\begin{aligned}\text{Interest rate}_{b,f,t} =& \beta_1 \text{carbon intensity bucket}_f \\ &+ \beta_2 \text{carbon intensity bucket}_f \times \alpha_t \\ &+ \theta_{b,t} + \theta_{f,t} + \theta_{b,f,t} \\ &+ \alpha_t + \alpha_b + \alpha_f + \epsilon_{b,f,t}\end{aligned} \tag{3}$$

With carbon intensity bucket$_f$ being a decouping of all firms into three buckets or five buckets, each of the same size. The reference group is always the middle group, composed of firms that have a carbon intensity close to the median of the sample. The specification used to present the results is the specification 2 in table 5, which is the specification with all control variables and a set of firm, bank and time (monthly) fixed effects.

Figure 17 presents the results of this non-linearity analysis using two different decomposition approaches. The left panel divides firms into three buckets based on carbon intensity: firms with high carbon intensity (top 33%), firms with medium carbon intensity (middle 33%, reference group), and firms with low carbon intensity (bottom 33%). The right panel offers a more granular approach with five buckets: very brown (top 20%), brown (top 20-40%), medium (middle 20%, reference group), green (bottom 20-40%), and very green (bottom 20%).

The results reveal striking non-linearities in climate risk pricing that were not apparent in our initial analysis. Looking at the three-bucket decomposition (left panel), we observe that from early 2021 to mid-2022, both high and low carbon intensity firms had coefficients that fluctuated around zero, suggesting no differential pricing based on carbon intensity during this period. However, starting in mid-2022, a clear divergence emerges with coefficients for low carbon intensity firms becoming increasingly negative, while those for high carbon intensity firms show no trend. This pattern indicates that banks began offering a significant "greenium" (lower interest rates) to low carbon intensity firms, while simultaneously charging a smaller "brown penalty" (higher interest rates) to high carbon intensity firms. The magnitude of the greenium appears substantially larger than the brown penalty, with coefficients for low carbon intensity firms reaching approximately -0.4 by mid-2023, compared to about 0.1 for high carbon intensity firms. The five-bucket decomposition (right panel) provides further nuance to this finding. Very green firms (bottom 20%) experience the largest interest rate discount, with coefficients reaching nearly -0.5 by late 2023. Green firms (bottom 20-40%) also receive substantial discounts, albeit slightly smaller. On the brown side, very brown firms (top 20%) face modest interest rate premiums, while the brown firms (top 20-40%) show coefficients that hover closer to zero with higher uncertainty bands.

This pronounced asymmetry suggests that banks' climate risk pricing strategies may be more focused on rewarding green firms than penalizing brown ones. Such behavior could reflect banks' strategic focus on expanding their green lending portfolios to meet sustainability targets or regulatory expectations, rather than directly penalizing carbon-intensive activities. It may also indicate that banks perceive more upside potential in financing green firms than downside risk in continuing to finance brown firms, at least at current carbon price levels.

The temporal pattern aligns with our previous dynamic analysis, showing minimal differentiation in 2021 and early 2022, followed by an accelerating divergence from mid-2022 onward. This timing coincides with increased regulatory pressure on financial institutions to disclose and manage climate-related risks, suggesting that policy and regulatory developments may be important drivers of this pricing behavior. These non-linear patterns have important implications for the effectiveness of financial markets in incentivizing decarbonization. The strong greenium observed suggests that firms may experience significant financial benefits from transitioning to lower-carbon activities, potentially accelerating the reallocation of capital toward sustainable economic activities.

4.2 When green meets green

The objective of this section is to examine how banks incorporate climate risk into corporate loan pricing and whether their sensitivity to climate-related financial risks depends on their own environmental profile. The analysis builds on the emerging literature that investigates the interaction between lender and borrower environmental characteristics. A key reference in this area is Degryse et al. (2023), who study the phenomenon of "green meets green," providing evidence that environmentally conscious banks tend to price loans differently depending on the carbon intensity of borrowing firms. We extend their approach by incorporating different classifications of green and brown banks and assessing whether the differential pricing effect has evolved over time.

To perform this analysis, we estimate a panel regression model where the interest rate spread on corporate loans is regressed on an interaction term between bank and borrower environmental characteristics, controlling for macroeconomic and firm-specific variables. Specifically, we differentiate banks based on their weighted average carbon intensity, considering the top 50% as "brown banks" and the bottom 50% as "green banks." We complement this approach by adopting the European Central Bank (ECB) Climate Stress Test (CST) classification to verify the robustness of our findings. I use the same regression as presented in esquation xxx but I divide the sample into two parts depending of the banks group: green banks or brown banks.

Figure 10 presents the estimated coefficients of the interaction term between bank and borrower environmental characteristics over time. The left panel (Approach 1) classifies banks based on their weighted average carbon intensity, while the right panel (Approach

2) relies on the ECB CST 2022 classification.

A key observation from both panels is the increasing divergence in the pricing of corporate loans between green and brown banks starting in 2022. In Approach 1, green banks exhibit a rising positive interaction term, indicating a growing preference for environmentally friendly borrowers. This suggests that green banks offer lower loan spreads to green firms, possibly reflecting a lower perceived credit risk or a strategic alignment with sustainability goals. In contrast, brown banks show a relatively flat interaction term, implying that they do not significantly differentiate pricing based on borrower environmental characteristics.

The results under Approach 2 reinforce these findings, albeit with a more pronounced initial decline in the interaction term for brown banks. This could indicate that brown banks initially responded to climate-related financial risks by tightening credit conditions for green firms before stabilizing their pricing strategy. Overall, both approaches confirm that the interaction effect has strengthened over time, aligning with the hypothesis that financial institutions are progressively internalizing climate risks into their lending decisions.

Our findings are consistent with Degryse et al. (2023), who document that green banks favor green firms through lower borrowing costs. However, our contribution extends their analysis by providing a dynamic perspective on this effect, illustrating how the green-on-green pricing differential has evolved in response to regulatory developments and growing climate risk awareness. Additionally, by employing alternative classifications of green and brown banks, we show that the observed patterns are robust to different measurement approaches.

These results have important implications for financial stability and policy. They suggest that banks increasingly differentiate borrowers based on environmental criteria, which may contribute to capital allocation shifts towards sustainable activities. However, the asymmetric response between green and brown banks also raises concerns about potential credit constraints for carbon-intensive firms, especially if brown banks continue to face regulatory pressure to decarbonize their portfolios. This dynamic warrants further research, particularly on the long-term consequences for firms' access to credit and investment decisions.

In sum, our analysis provides empirical evidence that banks' environmental preferences influence loan pricing, reinforcing the notion that climate risk is becoming a material factor in financial decision-making. This underscores the need for policymakers to consider the heterogeneity of banks' climate strategies when designing climate-related financial regulations.

4.3 Between or within sectors approach

A central question in the literature on climate finance is how banks incorporate transition risks into loan pricing. Two prevailing strategies have been identified: the sectoral approach, where banks offer lower interest rates to firms in less polluting sectors, and the within-sector approach ("best-in-class"), where banks differentiate between firms within the same sector, rewarding the greenest firms even in traditionally high-emission industries. The best-in-class approach ensures that banks continue to finance essential industries while encouraging sustainability improvements within them, rather than shifting financing away from high-emission sectors entirely. Understanding which of these strategies dominates is essential for assessing the financial sector's role in incentivizing corporate decarbonization.

To disentangle these two pricing mechanisms, I decompose firm-level carbon intensity into two components: a sectoral component, capturing the average carbon intensity of a firm's sector, and an idiosyncratic component, reflecting the deviation of a firm's emissions from its sectoral average. The average carbon intensity of a firm's sector is the one reported by all banks in average in the Fit-for-55 climate data collection, not computed myself based on the granular data I have, as the granular sample banks had to report might not be representative of the complete vision of banks of the whole sectors of activity. This decomposition allows me to assess whether banks primarily respond to sector-wide climate risk or whether they reward firms that outperform their peers in emission reductions within high-carbon industries. My approach builds on the work of Degryse et al. (2023), who explore the interaction between lender and borrower environmental profiles, extending their findings by incorporating a temporal dimension to assess shifts in pricing strategies over time.

$$
\begin{aligned}
\text{Interest rate}_{b,f,t} = & \beta_1 \text{Carbon intensity}_{f,sector} \\
& + \beta_2 \text{Carbon intensity}_{f,sector} \times \alpha_t \\
& + \beta_3 (\text{Carbon intensity}_f - \text{Carbon intensity}_{\text{f,sector}}) \\
& + \beta_4 (\text{Carbon intensity}_f - \text{Carbon intensity}_{f,sector}) \times \alpha_t \\
& + \theta_{b,t} + \theta_{f,t} + \theta_{b,f,t} \\
& + \alpha_t + \alpha_b + \alpha_f + \epsilon_{b,f,t}
\end{aligned} \tag{4}
$$

With $\text{Carbon}_{f,sector}$ being the average carbon intensity of a NACE 2 sector and thus $(\text{Carbon}_f - \text{Carbon}_{f,sector})$ being the idiosyncratic part of the carbon intensity, the part that is not explained by the sector. If the idiosyncratic component of the carbon intensity of a firm is negative, this means that the firm is greener that the average of its activity sector.

Figure 10 presents the estimated coefficients of the interaction term between bank and borrower environmental characteristics over time, distinguishing between the sectoral and idiosyncratic components of carbon intensity. Across all specifications, we observe a clear divergence in how banks price climate transition risk.

In Specifications 2 and 3, both the sectoral and idiosyncratic components exhibit increasing significance over time, suggesting that banks have progressively incorporated climate considerations into loan pricing since 2022. However, the sectoral effect remains consistently positive, indicating that firms operating in cleaner sectors receive preferential pricing, independent of their individual environmental performance. This confirms the existence of a sectoral approach, where banks allocate capital towards low-carbon industries.

Specifications 4 and 5 provide further insights into within-sector differentiation. The idiosyncratic carbon intensity coefficient rises more sharply, particularly from mid-2022 onwards, while the sectoral effect stabilizes. This dynamic suggests that, over time, banks have increasingly adopted a "best-in-class" approach, rewarding firms that reduce emissions relative to their sectoral peers. Notably, the within-sector effect is particularly pronounced in capital-intensive industries, where green investment signals lower transition risk exposure and regulatory compliance benefits. This result aligns with sustainable investment strategies observed in asset management, where best-in-class selection ensures that capital flows toward firms leading the transition within their respective industries rather than penalizing entire sectors.

Our results suggest that banks employ a dual strategy when pricing climate transition risk. Initially, banks favored firms in low-carbon sectors, reflecting broad sectoral risk assessment. However, as transition policies and climate disclosure frameworks evolved, within-sector differentiation became more pronounced, rewarding green leaders in polluting industries.

These findings contribute to the ongoing policy debate on climate risk integration in financial decision-making. The shift towards within-sector differentiation indicates that banks are increasingly considering firm-level decarbonization efforts, reinforcing the role of financial institutions in incentivizing corporate transition strategies. From a regulatory perspective, this evolution underscores the importance of transparent carbon disclosure frameworks to ensure that green leaders within high-emission industries are appropriately rewarded, thereby enhancing the effectiveness of climate finance policies.

5 Analysis of the green confusion

5.1 Uncertainty around carbon intensity estimation

Differential Bank Reactions to Climate Transition Risk Under Carbon Intensity Uncertainty Introduction The growing awareness of climate change impacts on financial stability has led banks to increasingly incorporate climate transition risk into their lending decisions. This section examines how banks price climate transition risk in corporate loans, specifically focusing on how uncertainty in carbon intensity measurements affects lending behavior. The analysis leverages multiple econometric specifications to demonstrate the robustness of the observed patterns across different thresholds and parameters.

Climate transition risk pricing in bank lending has emerged as a critical area of research. Previous studies (Ehlers et al., 2021; Bolton and Kacperczyk, 2021) have documented that financial institutions increasingly incorporate carbon emissions into lending decisions, though the methodologies and impact vary significantly across institutions. Jung et al. (2023) highlighted that data quality issues create substantial uncertainty in carbon accounting, potentially affecting financial decision-making. Importantly, Flammer and Bansal (2022) found that information disclosure quality significantly impacts the pricing of climate risk, while Krueger et al. (2020) demonstrated that investors struggle to price climate risk when faced with inconsistent or uncertain emissions data. However, limited research has examined how data uncertainty specifically affects bank lending decisions—a gap this analysis addresses.

Our approach examines how banks adjust their loan pricing based on the uncertainty of a firm's reported carbon intensity. We define uncertainty as the standard deviation of carbon intensity values reported by different banks for the same counterparty. Using fixed effects panel regressions (implemented via the felm function), we estimate the relationship between annualized agreed loan rates (ANNLSD$_{A}GRD_{R}T2)andcarbonintensitymeasures, interactedwi$

Firms are classified into two categories:

Low uncertainty: Standard deviation of reported carbon intensity below the median (or below the 75th percentile in specification 4) High uncertainty: Standard deviation of reported carbon intensity above the median (or above the 75th percentile in specification 4)

To ensure robustness, we employ multiple specifications:

Specifications 1-3 vary in fixed effects structure, using firm and bank fixed effects separately or firm-bank pair fixed effects Minimum thresholds of 2 or 3 banks ranking the same counterparty Different percentile thresholds (50th and 75th) for uncertainty classification.

The graphical evidence presented in Figures 13-16 reveals several key patterns in how banks price climate transition risk under different levels of carbon intensity uncertainty:

Divergent Trajectories: Across all specifications, we observe markedly different trajectories in the coefficient of the interbank term for high versus low uncertainty firms. This divergence becomes more pronounced from 2022 onward, suggesting an evolution in banks' climate risk assessment sophistication. Stronger Pricing for Low Uncertainty Firms: In all specifications, banks demonstrate a significantly stronger pricing of climate transition risk (higher coefficient values reaching 0.3-0.6) for firms with low carbon intensity uncertainty (blue lines). This is particularly evident in 2023-2024. By contrast, high uncertainty firms (orange lines) show relatively flat or slightly negative coefficients, typically in the range of -0.2 to 0.2. Temporal Evolution: For low uncertainty firms, we observe a distinct pattern: relatively flat or slightly negative coefficients through 2022, followed by a sharp upward trend in 2023, and a moderate decline or plateau in 2024. This temporal pattern is consistent across specifications 2 and 3 (panels a and b in each figure), with slight variations in magnitude. Specification Consistency: The observed pattern holds across different model specifications and minimum bank thresholds. When comparing specification 2 (which uses separate fixed effects) with specification 3 (which uses interacted fixed effects DBTR$_R IAD_C D_L E$: $CRDTR_R IAD_C D_L E), weseesimilarpatternsbutwithslightlyhighermagnitudesinspecification3, parti$ $Theconfidenceintervals(shadedareas)generallysupportthestatisticalsignificanceofthedifferencebet$ $2024.Thewiderbandsforhighuncertaintyfirms(orangeshading)furtherreflecttheinherentvariability$ $Ourregressionincludesbothsectoralcarbonintensity(log_intensity_sectoral)andfirm-specificdeviations$ $wideandfirm-specificeffects.Thechartssuggestthatbanksrespondmorestronglytosectoralcarboninte$ $leveltransitionriskmaybeeasiertopricewhendataqualityishigh.$

This evidence strongly suggests that banks exhibit greater caution when faced with uncertain carbon intensity data, preferring to apply stricter climate risk pricing when they have higher confidence in emissions measurements. The results are consistent across various robustness checks, including different fixed effects structures, minimum thresholds for bank observations, and percentile cutoffs for uncertainty classification.

The differential reaction of banks to carbon intensity uncertainty has several important implications: First, it underscores the critical importance of standardized, reliable climate data disclosure. The observed pricing differential creates an incentive for corporations to improve their emissions measurement and reporting practices to potentially benefit from more favorable lending terms. Second, the results suggest that climate risk may be systematically underpriced for firms with highly uncertain emissions profiles, potentially creating misallocation of capital and delayed climate transition in sectors with poor data quality. Third, the evolving pattern of coefficients indicates that banks' climate risk assessment capabilities are maturing, with a more sophisticated and nuanced approach emerging over the studied period. These findings contribute to our understanding of how information quality mediates the effectiveness of market-based climate transition mechanisms. The persistent uncertainty premium observed in lending decisions highlights the complementary role that regulatory standardization of emissions reporting could play in improving market efficiency. Future research should explore whether this uncertainty effect varies across industries, firm sizes, or geographic regions, and whether improved disclosure requirements tangibly reduce the uncertainty premium in bank lending decisions.

- When uncertainty is high, both sectoral carbon intensity and idiosyncratic carbon intensity have a lower impact on interest rates - Sectoral carbon intensity stay significant and positive even in case of high uncertainty, while idiosyncratic carbon intensity is the factor that tanks to zero in case of uncertainty. There thus seems to be a change of strategy banks adopt in case of high uncertainty: going from within sectors to between sectors, and only rely on sectoral values that could be perceived as more robusts than individual values.

5.2 Ability of banks to distinguish what is green and what is brown

The transition to a low-carbon economy presents significant financial risks for firms with carbon-intensive business models. As regulatory pressures intensify and carbon pricing mechanisms expand, financial institutions face increasing pressure to incorporate climate considerations into their lending practices. This section examines how does the pricing of climate transition risk identified before might depend on banks' own capacity to assess climate risks?

To do so, I use the same regression as presented in Equation 4 but I split the complete sample into two groups. The study employs two different specifications to classify banks as either "capable" or "non-capable":

In the first specification, for which the results are shown in Figure 17, banks are classified based on the number of flags received during the first submission of the Fit-for-55 template (FDC1). Banks that received fewer flags than the median are classified as "high-capacity banks" (shown in blue), while those that received more flags than the median are classified as "low-capacity banks" (shown in orange). This measure treats the total number of flags as a direct indicator of a bank's ability to properly assess and report climate-related information. In the second Specification, for which the results are depicted in Figure 18, an alternative classification is used based on the number of flags resolved between the first template submission (FDC1) and the last submission (FDC3). This approach focuses on banks' responsiveness and ability to correct identified issues. Banks that successfully resolved more flags are classified as "high-capacity banks," reflecting their greater adaptability and technical competence in addressing climate risk assessment challenges.

This bifurcation of the sample allows for direct comparison between how capable and non-capable banks price loans to carbon-intensive borrowers. The divergence in the coefficient patterns between the two groups (visible in both Figures 17 and 18) provides compelling evidence that banks' technical capacity meaningfully influences their ability to incorporate climate transition risk into loan pricing decisions. The sample split is particularly important for interpreting the interaction terms in the regression results (Table 1), where the coefficients on "Carbon intensity:capable bank:year" capture the differential pricing effect for capable banks relative to non-capable banks in each year. The consistency of results across both classification approaches strengthens the conclusion that bank capacity is indeed a crucial factor in determining how climate risks are priced in corporate lending markets. The sample consists of 63 banks for which the number of flags received is observed, with approximately 30 banks in each capacity category, ensuring sufficient sample size for statistical inference while allowing for a clear distinction between high and low-capacity institutions.

Capacity impact as much the between sector and within sector, but this effect is concentrated among green banks. Brown banks never price climate transition risk, but green banks do it even more when they are capable of understanding what is really green and what is brown.

The empirical analysis presented in Table 1 and Figures 17-18 reveals several key patterns in the relationship between carbon intensity and loan pricing across different types of banks. The results demonstrate a heterogeneous response to borrowers' climate transition risk that varies significantly based on bank characteristics and evolves over time.

As shown in Figure 17, there is a clear divergence in the pricing of carbon risk between high-capacity and low-capacity banks, with the distinction becoming more pronounced after 2022. High-capacity banks (blue line) demonstrate an increasing tendency to charge higher interest rates for carbon-intensive borrowers, while low-capacity banks (orange line) show a flat or slightly negative relationship. This pattern holds whether using sectoral carbon intensity (panel a) or idiosyncratic carbon intensity (panel b) as the independent variable. Looking at the regression results in Table 1, columns (1) and (2) contrast the pricing behavior of green banks versus brown banks. For green banks, the interaction terms between carbon intensity and capable bank indicators show positive and statistically significant coefficients across all years: 0.049 (significant at 1%) for 2022, 0.092 (significant at 5%) for 2023, and 0.088 (significant at 10%) for 2024. This indicates that capable green banks consistently apply a carbon premium in their loan pricing.

The results reveal a temporal dimension to the pricing of climate transition risk. The coefficient estimates for the interaction terms (Carbon intensity:capable bank:year) show an increasing trend from 2022 to 2023, suggesting that capable banks have progressively strengthened their carbon risk pricing over time. This temporal pattern is visible in both Figure 17 and Figure 18, where the divergence between high and low-capacity banks becomes more pronounced after 2022, coinciding with the intensification of climate policy discussions and implementation in the EU.

The findings remain robust across different model specifications with various fixed effects configurations. Columns (3) and (4) include bank-firm fixed effects, while columns (5) and (6) incorporate bank-time fixed effects. The persistence of the positive and significant interaction terms across these specifications reinforces the reliability of the observed relationship between bank capacity, carbon intensity, and loan pricing. Figure 18 provides additional confirmation by using an alternative measure of bank capacity based on flags resolved between the first template submission (FDC1) and the last (FDC3). The consistent divergence pattern between high and low-capacity banks across both measurement approaches strengthens the evidence for a capacity-dependent relationship in carbon risk pricing.

The positive coefficients on the interaction terms (Carbon intensity:capable bank:year) suggest that capable banks charge a risk premium for carbon-intensive borrowers. This premium can be interpreted as compensation for the elevated default risk associated with firms facing higher transition costs. For instance, the coefficient of 0.092 for capable green banks in 2023 implies that a one standard deviation increase in carbon intensity is associated with approximately 9.2 basis points higher interest rates for loans from capable green banks relative to other banks. The observed pricing differential aligns with risk-based pricing theory, where lenders adjust terms based on the expected probability of default and loss given default. As carbon-intensive firms face increasing regulatory costs and potential stranded asset risks, forward-looking banks incorporate these factors into their risk assessment models.

Several mechanisms may explain the observed differential pricing. First, high-capacity banks likely have superior risk assessment capabilities, enabling them to more accurately identify and price transition risks. Second, these banks may face different regulatory expectations or investor pressures regarding climate risk management. Third, high-capacity banks might have strategically positioned themselves to capture the green premium by developing specialized expertise in environmental risk assessment.

6 Conclusion

This study examines how European banks price climate transition risk in their corporate loan portfolios. By leveraging a unique dataset from European mandatory climate reporting, this paper provides novel insights into how banks perceive and incorporate carbon intensities of their debtors into lending decisions.

The empirical analysis confirms and extends several findings from the nascent literature on climate risk pricing in corporate lending. First, it documents that euro-area banks have been charging lower interest rates to firms with lower carbon emissions since at least 2022, even after controlling for credit risk through probability of default measures and employing comprehensive fixed effects structures across time, firms, and banks. Firms with lower carbon intensity benefit from reduced borrowing costs of approximately 20-40 basis points.

Second, the results demonstrate that this pricing effect is primarily driven by ”green banks” – institutions that actively promote climate transition through their lending policies. Banks that indicated no interest in climate risk pricing or developing climate scenario analysis during the 2022 ECB climate stress test, or that have a high credit portfolio weighted average carbon intensity do not in fact appear to price climate risk at all. This ”when green meets green” effect highlights the importance of bank-level sustainability commitments in translating climate considerations into concrete pricing decisions. Third, the dynamic temporal analysis reveals that the pricing of climate transition risk has strongly intensified since 2022-2023, suggesting growing integration of climate factors into lending decisions. This trend aligns with increasing regulatory pressure and market awareness regarding climate-related financial risks.

Building on the confirmations of these results from the literature, this study provides three new main contributions.

The first major contribution is identifying the specific mechanism through which climate risk pricing functions. Rather than imposing a ”brown punishment” (higher rates for carbon-intensive firms), banks predominantly implement a ”green premium” (lower rates for low-emission firms). This asymmetric approach suggests that banks view climate-friendly lending as an opportunity to support sustainable businesses rather than merely penalizing high emitters. I also find that banks simultaneously employ both between-sector and within-sector approaches to climate risk pricing. This ”best in class” methodology allows banks to reward greener firms within their respective industries while also accounting for sectoral differences in emission intensities. This nuanced approach demonstrates sophisticated risk assessment beyond simple sector-based exclusions. The prevalence of a green premium rather than a brown punishment suggests that banks may be responding more to opportunities in growing green markets than to perceived risks in carbon-intensive sectors. This aligns with Porter hypothesis extensions suggesting that environmental performance can be value-creating rather than merely cost-increasing.

The second contribution relates to the effects of uncertainty in carbon intensity measurements. When significant discrepancies exist between banks' perceptions of the same firms' carbon intensities (what is called ”green confusion” in the literature), the green premium substantially diminishes. This uncertainty primarily affects the within-sector ”best in class” approach, causing banks to rely more heavily on sectoral classifications when firm-level data appears unreliable. This finding connects to economic theories of information asymmetry and decision-making under uncertainty. When faced with noisy signals about firms' environmental performance, banks appear to revert to more conservative lending practices, reducing their willingness to offer preferential rates based on granular environmental metrics. The ”green confusion” effect indicates that information quality serves as a crucial constraint on efficient climate risk pricing. This connects to broader economic theories about information as a public good and suggests potential market failures in environmental data provision that may warrant regulatory intervention.

Finally, this analysis reveals that some banks lack adequate data and modeling infrastructure to effectively differentiate between green and brown firms. These banks received a high number of ”flags” by the European Central Bank when they submit their climate data reportings These institutions appear unable to price climate transition risk regardless of their stated commitments. Importantly, this limitation predominantly affects green banks, as those without environmental commitments (”brown banks”) consistently fail to price climate risk regardless of their technical capabilities. The differential impact of data limitations across bank types suggests that technical capacity and institutional commitment are complementary inputs in effective climate risk pricing.

These findings have several implications. For regulators, the identified ”green confusion” effect highlights the urgent need for standardized, reliable climate reporting frameworks to reduce market uncertainty. Policy interventions that improve environmental data quality and accessibility could enhance market efficiency by allowing banks to more confidently reward genuinely sustainable firms. For financial institutions, these results underscore the importance of investing in robust climate risk assessment capabilities. Banks with stronger data infrastructure and clearer sustainability commitments appear better positioned to implement sophisticated climate risk pricing strategies, potentially gaining competitive advantages in increasingly climate-conscious markets. Implementing exercises such as new mandatory climate data collection or climate stress test might appears useful to improve the pricing of climate risk by banks, especially the one that want to become greener and that are currently limited by their green capacities. For researchers, this study opens several avenues for future investigation, including exploring how the identified pricing mechanisms evolve over longer time horizons, examining potential spillover effects to other financial products, and investigating whether similar patterns exist in other geographic regions with different regulatory landscapes.

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APPENDIX

A Data and descriptive statistics

A.1 Variables description

Variable	Description
Interest rate	Weighted average interest rate that is individually agreed between the reporting agent (creditor) and the debtor (usually a non-financial corporation) for all their loans, converted to an annual basis and quoted in percentages per annum ('Interest rate' in AnaCredit). The interest rate covers all interest payments on loans, but no other charges that may apply. The weights correspond to the total outstanding nominal amount of each loan between a creditor and a debtor, for a given date.
Carbon intensity (log)	Ratio between the Scope 1 greenhouse gas emissions of a debtor ("Absolute S1 GHG emissions" in Fit-for-55 data collection) and the debtor's total revenue ("Total revenues" in FF55), following the formula proposed by ECB for the Analytical indicators on carbon emissions. Absolute Scope 1 greenhouse gas emissions (tCO2e) are defined as the total amount of direct greenhouse gas emissions that are emitted from sources that are controlled or owned by an organisation over a specific period (e.g., emissions produced by manufacturing processes, burning diesel fuel in trucks, fugitive emissions such as methane emissions from coal mines, or production of electricity by burning coal). It is reported by each bank for each of their largest counterparties at the end of 2022. Total revenues are defined as the figure reported by the obligor in the Income Statement (in € million).

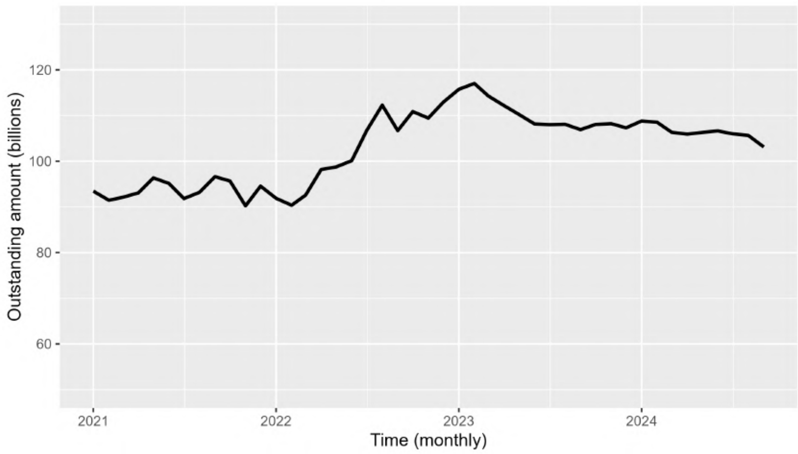
PD (log)	”Probability of default” in Anacredit. It corresponds to the PD over one year reported by a creditor adopting an internal ratings–based approach (IRBA) for a debtor. It is calculated in accordance with the requirements specific to PD estimation as laid down in the CRR and thus estimated with a through–the–cycle it (TTC) perspective. PD range between 0 and 1.
Maturity (log)	Weighted residual maturity of loans until their ”legal final maturity date” in Anacredit in days
Performing	Weighted average of all ”Performing status of the instrument” in Anacredit, a non-performing loan being equal to 1.
Impairment ratio	Ratio in Anacredit between the total ”accumulated impairment amount” reported by a creditor for all loans of a debtor and the total ”outstanding nominal amount” of these loans.
Protection ratio	Ratio in Anacredit between the total ”protection allocated value” reported by a creditor for all loans of a debtor and the total ”outstanding nominal amount” of these loans.
Outstanding amount (log)	”Outstanding nominal amount” in Anacredit. It is defined as the principal amount outstanding at the end of the reporting reference date, 14 including unpaid past due interest but excluding accrued interest. The outstanding 15 nominal amount must be reported net of write-offs and write-downs as determined by 16 the relevant accounting practices
CET1 ratio	Corep reporting template C03.00, row 0010 ”CET1 Capital ratio”
NPL ratio	Ratio between Finrep reporting template F18.00, row 0120 ”Loans and advances, Non-financial corporations”, column 0060 ”Non-performing”, and Finrep reporting template F18.00, row 0120 ”Loans and advances, Non-financial corporations”, column 0010 ”Nominal amount”

Provisions ratio	Ratio between Finrep reporting template F18.00, row 0120 ”Loans and advances, Non-financial corporations”, column 0120 ”of which: impaired”, and Finrep reporting template F18.00, row 0120 ”Loans and advances, Non-financial corporations”, column 0010 ”Nominal amount”.
Total assets	Finrep reporting template F01.00, row 0380 ”Total assets”.
ROA	Return-on-assets, ratio between Finrep reporting template F02.00, row 0670 ”Profit or (-) loss for the year”, and Total assets.
Assets (log)	”Total assets” in Anacredit, corresponds to the total assets of a counterparty reported in units of euro.
Turnover (log)	”Annual turnover” in Anacredit, corresponds to the annual turnover (sales) of a counterparty reported in units of euro.
Date	Monthly observation between January 2021 and September 2024.
Sector	”NACE 2 sector” of a counterparty in FF55.
Creditor	Debtors are identified through their LEI (Legal Entity Identifier) as indicated in the sample list published by EBA. Banks are consolidated at the highest level as indicated in the template guidance.
Debtor	Creditors are identified through their LEI (Legal Entity Identifier) and their RIAD (Register of Institutions and Affiliates Database code) as reported by banks in FF55. No consolidation is done as FF55 collection only covers the immediate borrowers of the bank as indicated in the template guidance.

Uncertainty	Standard deviation of all carbon intensities (log) reported by all banks for the same counterparty.
Flags	Number of flags received by each bank by the ECB during the first quality control phase of the data collection Fit-for-55. A flag indicates a missing value, an outlier value (in absolute or in relative compared to its peers) or a value that is too far away from what observed the ECB itself based on the climate data providers it have access to. The ECB thus ask the bank to justify its reporting or to correct it.

A.1.1 Description of the final sample

Figure 1: Total outstanding amount covered in the sample



Note: This chart reports the total outstanding amount (in billions of euros) between January 2021 and September 2024 of all credit relationships that are part of the final database use for the econometric analysis, after removing all rows with missing values and applying all filters described in the Section 2

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Table 1: French Fit-for-55 data collection participants

Name	LEI
BNP Paribas S.A.	R0MUWSFPU8MPRO8K5P83
BofA Securities Europe SA	549300FH0WJAPEHTIQ77
Bpifrance	969500STN7T9MRUMJ267
Confédération Nationale du Crédit Mutuel	9695000CG7B84NLR5984
Groupe BPCE	FR9695005MSX1OYEMGDF
Groupe Crédit Agricole	FR969500TJ5KRTCJQWXH
HSBC Continental Europe	F0HUI1NY1AZMJMD8LP67
La Banque Postale	96950066U5XAAIRCPA78
RCI Banque SA	96950001WI712W7PQG45
SFIL S.A	549300HFEHJOXGE4ZE63
Société Générale S.A.	O2RNE8IBXP4R0TD8PU41 FR

Note: This table reports the list of banking groups that participated to the EBA/ECB climate data collection "Fit-for-55" in 2023/2024 and of which the granular reportings are used to constitute the granular database about climate transition risk that is then merged with Anacredit and the other databases for this study. The final database is composed of banks that lend to the firms reported by these 11 french banks even if they are not part of this list.

Table 2: Percentage of outstanding amount per top 5 country of creditor and debtor

Country	Of the creditor	Of the debtor
FR	35%	33%
DE	18%	12%
IT	11%	12%
US	Not in top 5	9%
NL	10%	4%
ES	9%	Not in top 5
Other	28%	30%
Total	100%	100%

Note: This table reports the total outstanding amount of all loans in the sample and presents it by country of the creditors in column 2 and country of the debtors in column3. Only the top 5 countries are presented.

A.2 Descriptive statistics

Table 3: Complete Descriptive Statistics

Statistic	Dimension	Source	Min	Pctl(25)	Mean	Pctl(75)	Max	Median	St. Dev.
Carbon intensity (log)	Debtor	Fit-for-55	-2.020	2.076	3.805	5.527	11.363	3.384	2.383
Uncertainty	Debtor	Fit-for-55	0.000	0.072	0.942	1.560	4.050	0.633	0.976
Number of flags FDC1	Bank	Fit-for-55	0	56	156.058	208	1,788	140	161.161
Interest rate	Creditor x debtor x date (monthly)	Anacredit	0.000	0.989	2.397	3.626	9.140	1.610	1.944
Probability of default	Creditor x debtor x date (monthly)	Fit-for-55	0.00000	0.002	0.054	0.017	1.000	0.005	0.194
Maturity (log)	Creditor x debtor x date (monthly)	Anacredit	0.000	6.468	6.859	7.491	9.154	7.054	1.258
Non performing status	Creditor x debtor x date (monthly)	Anacredit	0.000	0.000	0.012	0.000	1.000	0.000	0.109
Impairment ratio	Creditor x debtor x date (monthly)	Anacredit	0.000	0.000	0.007	0.0002	43.215	0.000	0.170
Protection ratio	Creditor x debtor x date (monthly)	Anacredit	0.000	0.000	0.631	0.698	8.000	0.000	1.513
Outstanding amount (log)	Creditor x debtor x date (monthly)	Anacredit	5.566	14.796	16.004	17.274	22.385	16.106	1.782
Firm's total assets (log)	Debtor x date (annually)	Anacredit	22.133	27.423	27.410	27.967	28.649	27.521	0.901
Firm's turnover (log)	Debtor x date (annually)	Anacredit	0.000	17.026	18.013	20.606	29.315	18.880	4.947
CET1 ratio	Creditor x date (quarterly)	Corep	0.100	0.149	0.158	0.166	0.443	0.158	0.022
NPL ratio	Creditor x date (quarterly)	Corep	0.00000	0.034	0.039	0.043	0.250	0.039	0.011
Provisions ratio	Creditor x date (quarterly)	Finrep	0.000	0.033	0.037	0.041	0.141	0.038	0.010
ROA	Creditgor x date (quarterly)	Finrep	-0.006	0.001	0.003	0.004	0.020	0.002	0.002

Note: This table reports the dimension and source of all variables used in the study, as well as statistics about the distribution of the values for each variable.

Table 4: Comparison of green and brown firms

	Brown firms	Green firms	Difference of means	P-value
Carbon intensity (log)	5.706	2.010	3.695	0.000
Uncertainty	1.359	0.779	0.580	0.000
Number of flags FDC1	137.710	138.462	-0.751	0.894
Interest rate	3.875	3.656	0.219	0.010
Probability of default	0.075	0.049	0.026	0.008
maturity (log)	6.782	6.810	-0.029	0.570
Protection ratio	0.741	0.686	0.055	0.367
Outstanding amount (log)	16.234	16.217	0.017	0.800
CET1 ratio	0.157	0.157	0.000	0.921
NPL ratio	0.039	0.039	-0.001	0.064
Provisions ratio	0.037	0.038	-0.001	0.014
ROA	0.001	0.001	0.000	0.880
Firms's total assets (log)	27.506	27.491	0.015	0.664
Firm's turnover (log)	17.301	17.667	-0.366	0.078

Note: This table reports the average value for each variable for the firms that are part of the "green firms" group, and the "brown firms groups". Firms are classified green or brown based on their carbon intensity: firms with a carbon intensity inferiot to the median are classified as green, and inversely. The P-value corresponds to a p-value of a two-sample Student's t-Test, between the values distribution for a given variable among the green firms and the brown firms.

A.2.1 Descriptive statistics about carbon intensity

Figure 2: Histogram of
carbon intensity

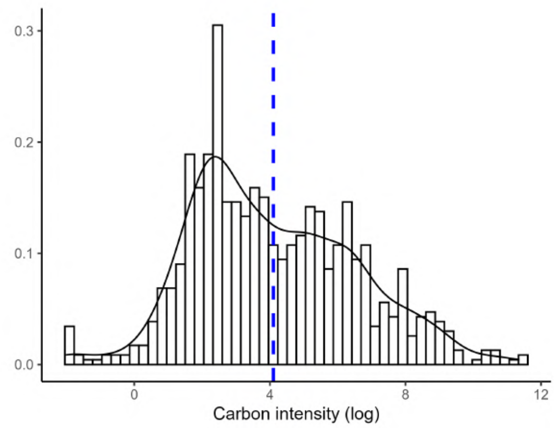
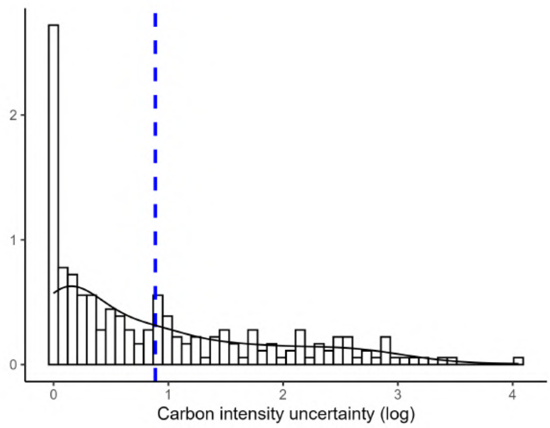


Figure 3: Histogram of
carbon intensity uncertainty



Note: These histograms display the distribution of carbon intensity values on a logarithmic scale (Figure 5a) as well as the distribution of carbon intensity uncertainty (Figure 5b). The smooth curve overlaid on the bars represents the density function of the distribution. The vertical blue dashed lines marks indicate the average value of each distribution. Carbon intensity uncertainty is defined as the standard deviation of all carbon intensities reported by different banks for the same firm, only firms with at least two observations are considered for Figure 5b. The distribution of the number of counterparties reporting a climate value per firm in the final sample based on the Fit-for-55 climate data reporting is presented in Table 5.

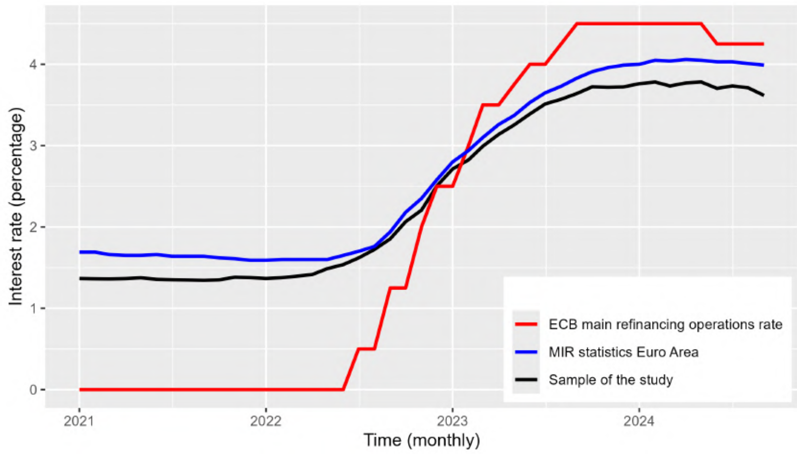
Table 5: Number of counterparties depending on the number of banks reporting them

Number of banks reporting a counterparty	1	2	3	4	4	5	6	7	8	Total
Number of counterparties reported	915	162	52	17	4	3	0	0	1	1154
Percentage of counterparties reported	79.3%	14.0%	4.5%	1.5%	0.3%	0.3%	0%	0%	0.1%	100%

Note: This table presents the distribution of the number of counterparties reporting a climate value per firm in the final sample based on the Fit-for-55 climate data reporting.

A.2.2 Time variation of interest rate

Figure 4: Comparison of interest rate in the sample and the whole corporate loan market

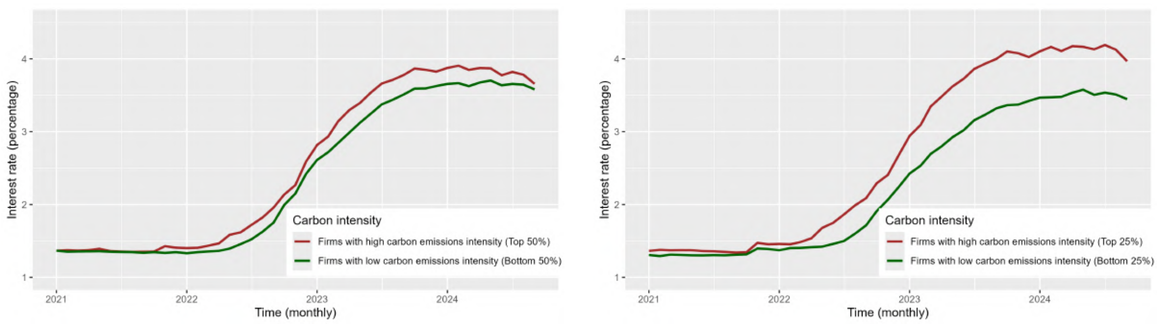


Note: This chart tracks the evolution of three key interest rate indicators from 2021 through early 2024 on a monthly basis. The y-axis represents interest rates (percentage), while the x-axis shows time. The red line represents the ECB main refinancing operations rate. The blue line shows the MIR (Monetary financial Institution interest Rate) statistics for the Euro Area M.U2.B.A20.A.R.A.2240.EUR.O. The black line depicts the interest rate for the study's sample, which closely tracks the Euro Area MIR statistics but consistently remains slightly lower throughout the period.

Figure 5: Interest Rate Differentials by Carbon Intensity

(a) Large definition:
Top 50% vs Bottom 50%

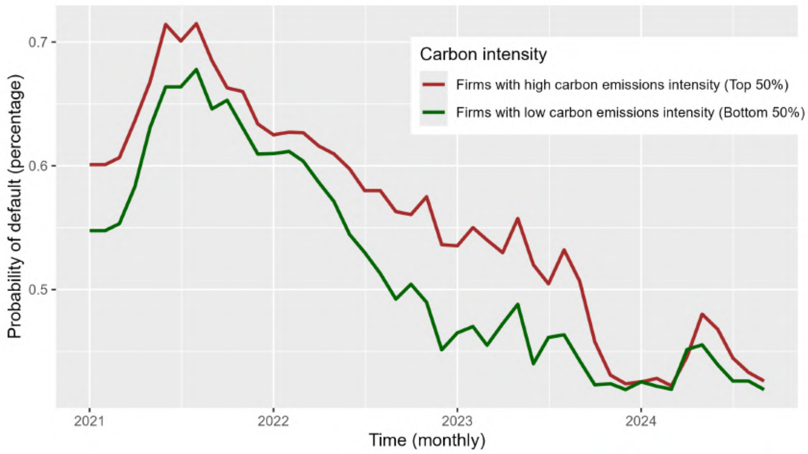
(b) Narrow definition:
Top 25% vs Bottom 25%



Note: This figure illustrates the relationship between a firm's carbon intensity and the interest rates they face. (a) Broad Classification: The red line represents the average interest rate for firms in the top 50% of carbon emitters ("high carbon intensity"), while the green line shows the average interest rate for firms in the bottom 50% ("low carbon intensity"). (b) Narrow Classification: This panel repeats the analysis but focuses on the extreme tails of the carbon intensity distribution. The red line depicts the average interest rate for firms in the top 25% of carbon emitters, and the green line represents the average interest rate for firms in the bottom 25%. The x-axis represents time in months, and the y-axis represents the interest rate as a percentage.

A.2.3 Time variation of probability of default

Figure 6: Probability of default of green and brown firms



Note: This figure illustrates the relationship between a firm's carbon intensity and the average probability of default reported by banks. The red line represents the average interest rate for firms in the top 50of carbon emitters ("high carbon intensity"), while the green line shows the average interest rate for firms in the bottom 50% ("low carbon intensity"). The x-axis represents time in months, and the y-axis represents the interest rate as a percentage.

B Results

B.1 Cross-section OLS

Table 6: Estimation of the impact of climate transition risk on corporate loans interest rate

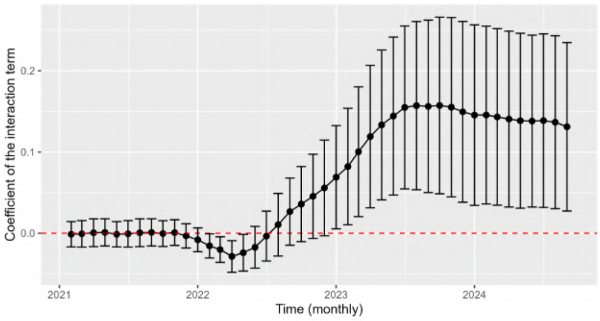
	Interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon intensity	0.038*	0.081***	0.082***	0.087***	0.096***	0.081***
	(0.020)	(0.024)	(0.024)	(0.026)	(0.024)	(0.024)
Probability of default	0.097***	0.096***	0.094***	0.088***	0.093***	0.089***
	(0.026)	(0.022)	(0.022)	(0.024)	(0.022)	(0.023)
Maturity	0.100***	0.094***	0.091***	0.098**	0.084***	0.088***
	(0.036)	(0.031)	(0.030)	(0.041)	(0.029)	(0.032)
Non-performing loan	−0.072	0.011	0.013	0.041	0.095	0.039
	(0.176)	(0.112)	(0.103)	(0.103)	(0.098)	(0.083)
Impairment ratio	0.052	0.054*	0.051	0.027	0.029	0.034
	(0.040)	(0.029)	(0.030)	(0.019)	(0.030)	(0.034)
Protection ratio	0.046***	0.032**	0.033**	0.017	0.048***	0.038***
	(0.014)	(0.014)	(0.014)	(0.020)	(0.015)	(0.014)
Outstanding amount	0.029	0.009	0.008	0.018	0.007	−0.004
	(0.037)	(0.028)	(0.028)	(0.035)	(0.026)	(0.028)
Firm Sector Fixed effects		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank-Sector Fixed effects				*Yes*		
Sector-Time Fixed effects					*Yes*	
Bank-Time Fixed effects						*Yes*
Bank controls			*Yes*	*Yes*	*Yes*	*Yes*
Firm controls			*Yes*	*Yes*	*Yes*	*Yes*
Observations	131,653	131,653	131,653	131,653	131,653	131,653
R^2	0.490	0.556	0.565	0.705	0.624	0.653
Adjusted R^2	0.488	0.552	0.561	0.695	0.588	0.607

Note: This table reports the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions estimated as presented in Equation 1. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. All regressions include bank and time fixed effects. All regressions include firm sector fixed effects except specification (1). Specifications (4) contains bank-sector fixed effects, specification (5) has firm sector-time fixed effects and specification (6) has bank-time fixed effects. The sector of the debtor is the NACE 2 group sector as constitued in the Fit-for-55 template. Specifications (3) to (6) have bank-date and firm-date control variables (CET1 ratio, NPL ratio, provisions ratio, ROA, total assets (log) of the debtor and its annual turnover (log). All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. Robust standard errors clustered at the bank-time level are reported in parentheses below the respective coefficient estimate. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

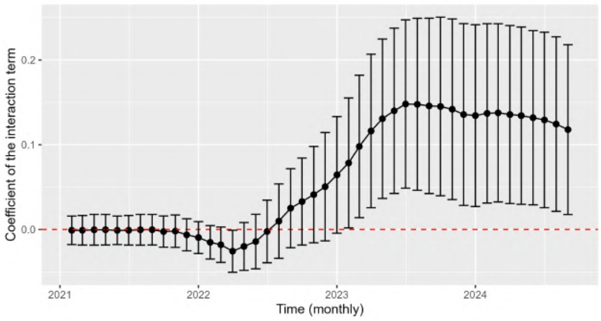
B.2 Dynamic analysis

Figure 7: Dynamic estimation of the impact of climate transition risk on corporate loans interest rate

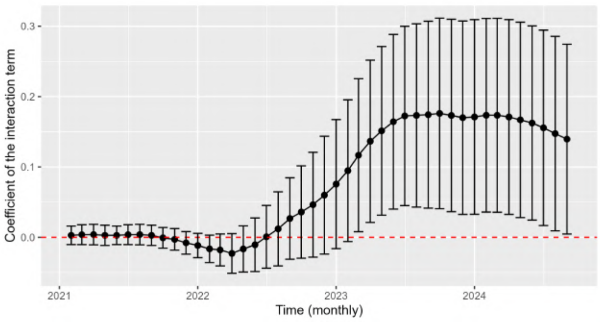
(a) Specification 2



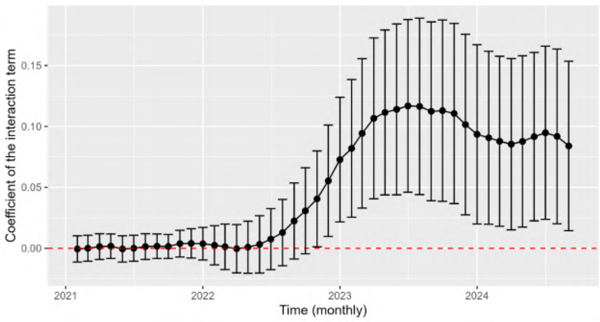
(b) Specification 3



(c) Specification 4



(d) Specification 6



Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 2. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

Table 7: Dynamic estimation of the impact of climate transition risk on corporate loans interest rate

	Interest rate				
	(1)	(2)	(3)	(4)	(5)
Carbon intensity:2022	0.019	0.019	0.020	0.023	0.025
	(0.023)	(0.023)	(0.024)	(0.029)	(0.018)
Carbon intensity:2023	0.147**	0.145**	0.138**	0.162**	0.106***
	(0.055)	(0.055)	(0.053)	(0.065)	(0.036)
Carbon intensity:2024	0.136**	0.137**	0.130**	0.155**	0.085**
	(0.056)	(0.056)	(0.054)	(0.069)	(0.036)
Probability of default		0.045*	0.044*	0.050*	0.031
		(0.023)	(0.023)	(0.028)	(0.021)
Maturity		0.105***	0.102***	0.126***	0.104***
		(0.018)	(0.018)	(0.022)	(0.019)
Non-performing loan		−0.075	−0.066	−0.020	−0.044
		(0.119)	(0.109)	(0.095)	(0.076)
Impairment ratio		0.042**	0.038**	0.019**	0.022
		(0.017)	(0.018)	(0.007)	(0.022)
Protection ratio		0.020	0.022*	−0.010	0.024*
		(0.012)	(0.012)	(0.022)	(0.013)
Outstanding amount		−0.015	−0.018	0.093**	−0.032*
		(0.017)	(0.016)	(0.037)	(0.017)
Firm Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank-Firm Fixed effects				*Yes*	
Bank-Time Fixed effects					*Yes*
Bank controls			*Yes*	*Yes*	*Yes*
Firm controls			*Yes*	*Yes*	*Yes*
Observations	131,653	131,653	131,653	131,653	131,653
R^2	0.653	0.655	0.664	0.814	0.746
Adjusted R^2	0.649	0.651	0.660	0.805	0.711

Note: This table reports the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 2. The columns (2) to (5) of this table corresponds to the results presented in Figure 7 but this table gives additional information. Monthly date fixed effects is replaced by a year fixed effects in order to reduce the number of variables and be able to presents the results in this synthetic table. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. Robust standard errors clustered at the bank-time level are reported in parentheses below the respective coefficient estimate. *p<0.1; **p<0.05; ***p<0.01

B.3 Robustness: matching methodology

Matching methodology

In order to address potential endogeneity concerns in our analysis of climate risk pricing, I implement a matching methodology that pairs green firms with comparable brown firms based on key financial and structural characteristics. This approach helps isolate the effect of carbon intensity on loan pricing by controlling for other firm-specific factors that might simultaneously influence both carbon emissions and interest rates. The matching procedure follows these steps: First, for each firm, I calculate standardized measures of default probability and firm total outstanding amount at the beginning of 2021 (first date in our sample) by subtracting the mean and dividing by the standard deviation to ensure comparability across different scales. Secondly, I apply the matching algorithm on debtors which is a combination of exact matching on the activity sector NACE 2, the institutional sector ESA and the country of the debtor, as well as a mahalanobis distance minimisation on two main variables: the probability of default and the size, computed as the logarithm of the total outstanding amount of a debtor. The minimisation of mahalanobis distance is done only within firms of the same activity sector, institutional sector and country. For each green firm, I select the brown firm with the lowest matching score, representing the closest match in terms of default risk and size within the same country, sector, and industry. It is a selection with replacement, so multiple green firms can be matched with the same brown firm. To account for cases where a brown firm might be matched to multiple green firms, I implement a weighting system. Each brown firm receives a weight equal to the number of green firms it matches with.

The efficacy of this matching approach is demonstrated through comparative analysis of key financial metrics (default probability and size) between the unmatched and matched samples as presented in Table 8 below. The weighted medians of these characteristics show substantial convergence between green and brown firms in the matched sample regarding probability of default. However, the exact matching condition leads to a reduction of convergence regarding the total outstanding amount of loans of debtors.

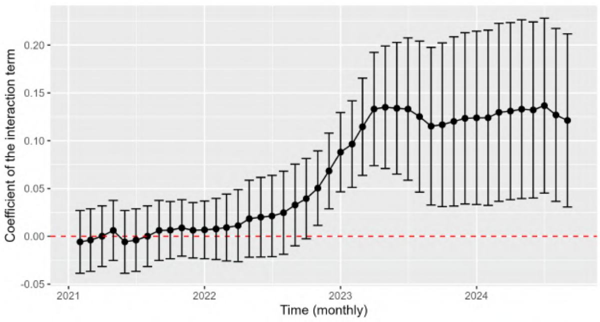
Table 8: Descriptive statistics of the green and brown firms before and after matching

	Without matching			With matching		
	Green	Brown	Difference	Green	Brown	Difference
Probability of default	0.437%	0.6%	0.163%	0.529%	0.394%	0.135%
Total outstandding amount (log)	19.22	18.96	0.35	19.13	18.7	0.42
Activity sector NACE 2	Different			Same		
Institutional sector ESA	Different			Same		
Country	Different			Same		

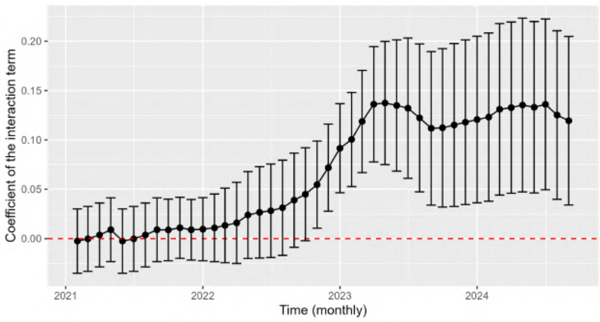
Notes: "Green" and "Brown" refers to firms's groups based on their carbon intensity. Green firms are the one with a carbon intensity lower than the median, while browns firms are firms with a carbon intensity higher than the median. "Without matching" shows the raw differences between the groups in the complete sample and "With matching" shows the differences after applying the matching technique described in Section B.3 to ensure the groups are more comparable on certain characteristics. The probability of default of debtors is expressed as a percentage and "Total outstanding amount (log)" is the average natural logarithm of the total outstanding amount of the credit relationships of the firms. The activity sector NACE2 and the country are the one of the debtor as reported in the template of the climate data collection Fit-for-55. The institutional sectors ESA of the debtors come from Anacredit.

Figure 8: Dynamic estimation of the impact of climate transition risk on corporate loans interest rate with matching

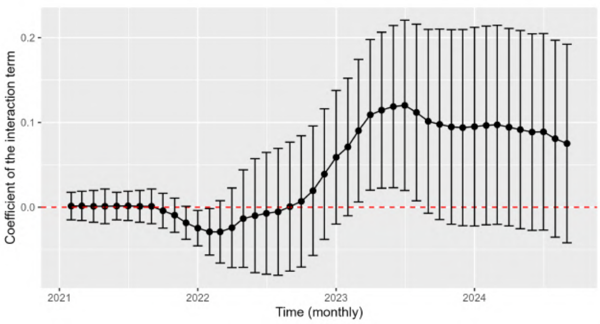
(a) Specification 2



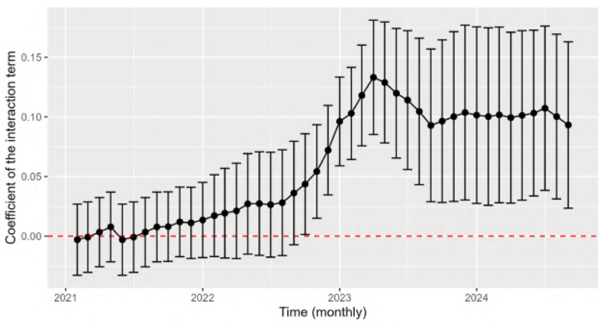
(b) Specification 3



(c) Specification 4



(d) Specification 6



Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate using the matched sample, from OLS regressions as presented in Equation 2. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

Table 9: Dynamic estimation of the impact of climate transition risk on corporate loans interest rate with matching

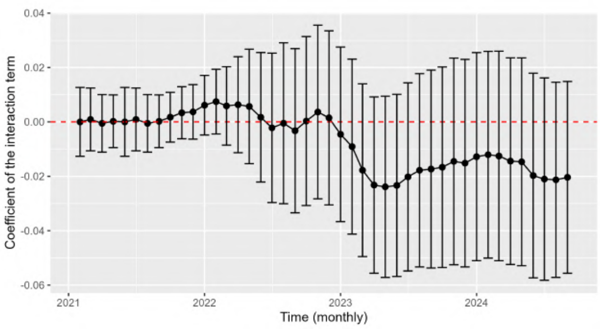
	Interest rate				
	(1)	(2)	(3)	(4)	(5)
Carbon intensity:2022	0.036	0.040*	0.042*	0.016	0.043***
	(0.022)	(0.021)	(0.022)	(0.036)	(0.015)
Carbon intensity:2023	0.133***	0.125***	0.121***	0.109**	0.108***
	(0.046)	(0.045)	(0.043)	(0.054)	(0.039)
Carbon intensity:2024	0.137**	0.126**	0.124**	0.091	0.093**
	(0.053)	(0.052)	(0.049)	(0.062)	(0.042)
Probability of default		0.056	0.059	0.079*	0.054
		(0.037)	(0.037)	(0.042)	(0.036)
Maturity		0.119***	0.116***	0.088**	0.138***
		(0.030)	(0.030)	(0.034)	(0.030)
Non-performing loans		−0.098	−0.093	−0.026	−0.109
		(0.149)	(0.145)	(0.092)	(0.143)
Impairment ratio		0.265	0.248	0.069	0.267
		(0.263)	(0.261)	(0.190)	(0.321)
Protection ratio		0.048*	0.051*	0.009	0.054**
		(0.025)	(0.025)	(0.027)	(0.025)
Outstanding amount		−0.010	−0.014	0.171***	−0.036
		(0.041)	(0.040)	(0.048)	(0.042)
Firm Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank-Firm Fixed effects				*Yes*	
Bank-Time Fixed effects					*Yes*
Bank controls			*Yes*	*Yes*	*Yes*
Firm controls			*Yes*	*Yes*	*Yes*
Observations	77,650	77,650	77,650	77,650	77,650
R^2	0.607	0.611	0.620	0.802	0.709
Adjusted R^2	0.602	0.606	0.615	0.793	0.657

Note: This table reports the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 2. The columns (2) to (5) of this table corresponds to the results presented in Figure 8 but this table gives additional information. Monthly date fixed effects is replaced by a year fixed effects in order to reduce the number of variables and be able to presents the results in this synthetic table. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. Robust standard errors clustered at the bank-time level are reported in parentheses below the respective coefficient estimate. *p<0.1; **p<0.05; ***p<0.01

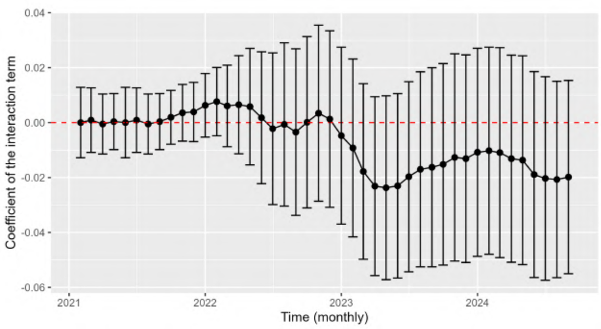
B.4 Dynamic analysis - Impact on credit relationship volumes

Figure 9: Dynamic estimation of the impact of climate transition risk on outstanding amount

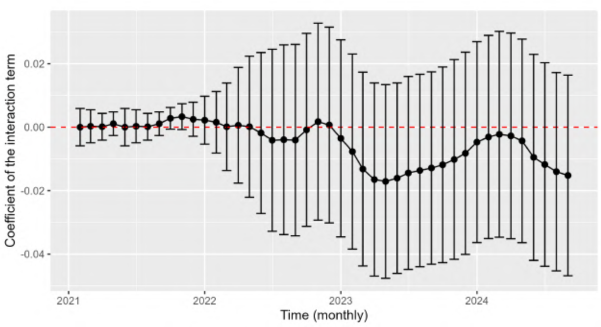
(a) Specification 2



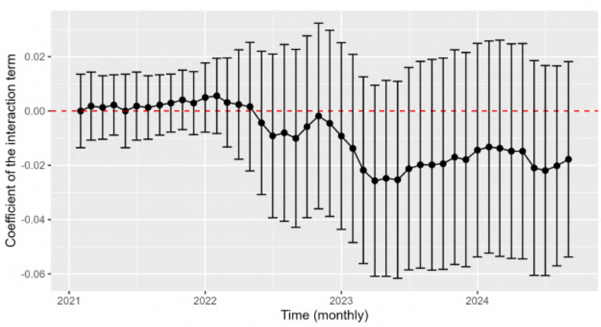
(b) Specification 3



(c) Specification 4



(d) Specification 6

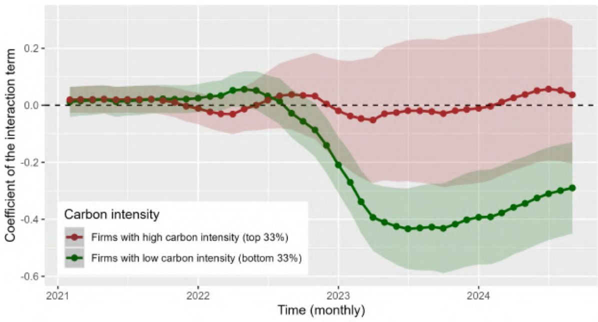


Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on outstanding amount, from OLS regressions as presented in Equation 2. The dependent variable is the total outstanding amount of all corporate loans between the reporting agent (bank) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy ”carbon intensity” expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects and the outstanding amount is removed for the independent variables. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

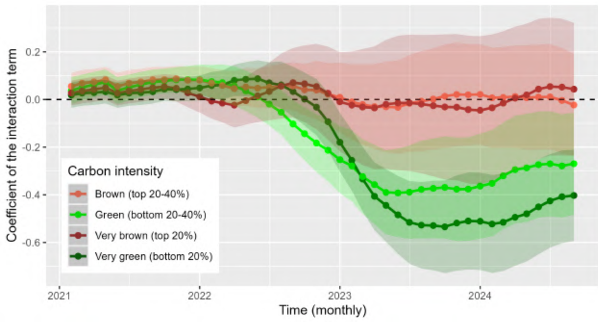
B.5 Analysis of the non-linearity in the relationship between climate transition risk and corporate loans interest rate

Figure 10: Dynamic estimation of the impact of climate transition risk on corporate loans interest rate

(a) Decomposition in three buckets



(b) Decomposition in five buckets

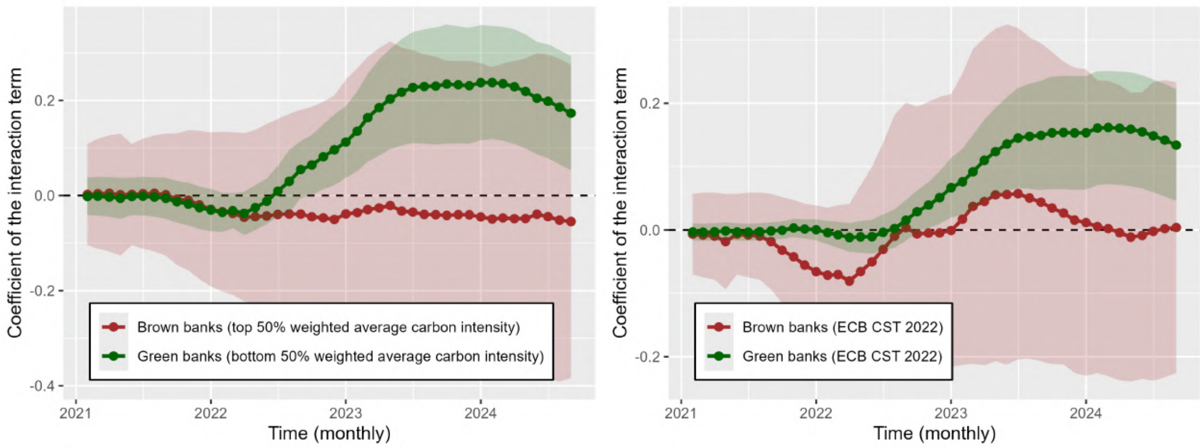


Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate using the matched sample, from OLS regressions as presented in Equation 3. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is a categorical variable indicating a group of firms depending on their climate transition risk proxy "carbon intensity". The left panel divides firms into three buckets based on carbon intensity: firms with high carbon intensity (top 33%), firms with medium carbon intensity (middle 33%, reference group), and firms with low carbon intensity (bottom 33%). The right panel offers a more granular approach with five buckets: very brown (top 20%), brown (top 20-40%), medium (middle 20%, reference group), green (bottom 20-40%), and very green (bottom 20%).The specification used corresponds to the specification (3) presented in Table 6. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

B.6 When green meets green

Figure 11: Analysis of the differentiated impact of climate transition risk and corporate loans interest rate depending on banks' greenness

(a) Approach 1 (b) Approach 2

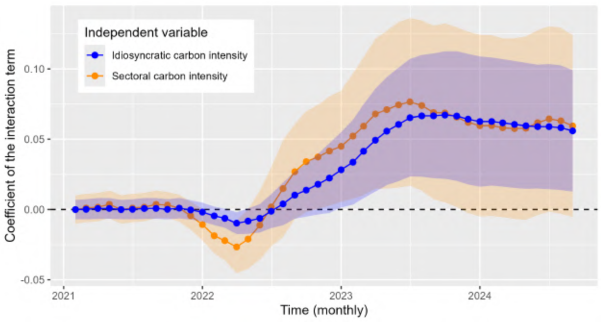


Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate using the matched sample, from OLS regressions as presented in Equation 2. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The estimation of the regression is done in two subsamples: the brown line presents the results for the estimation using only banks classified as brown, and the red line presents the results using only banks classified as green. The left panels defines being a green bank by having a weighted average carbon intensity inferior to the median. The right panel defines being a green bank by having been rated by the ECB one of the two best grades out of four in the module 1 of the ECB climate stress test of 2022. The specification used corresponds to the specification (3) presented in Table 6. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

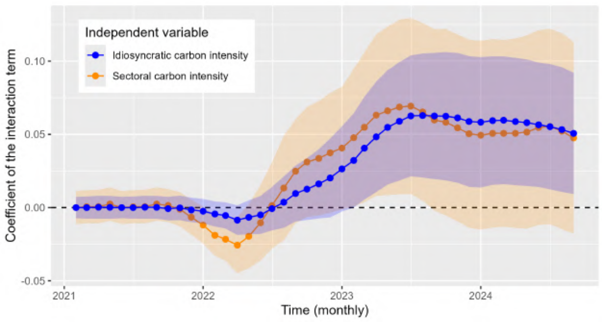
B.7 Analysis of the approach taken by banks: between or within sectors

Figure 12: Analysis of the differentiated impact of climate transition risk and corporate loans interest rate depending on the approach adopted by banks

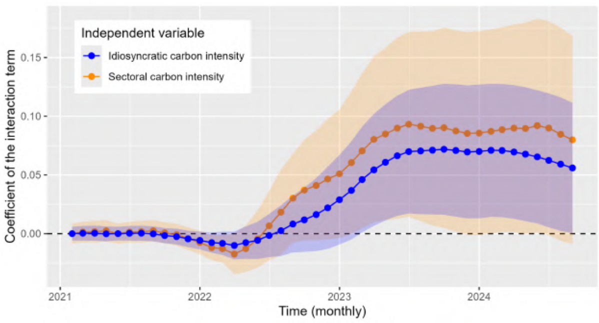
(a) Specification 2



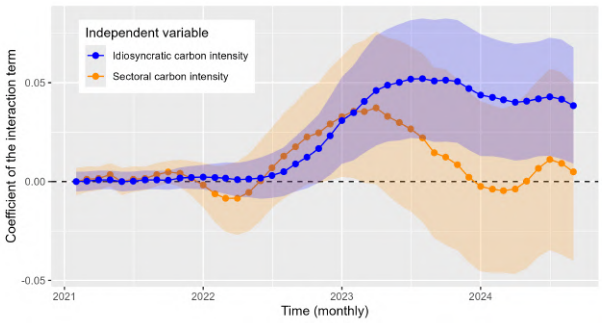
(b) Specification 3



(c) Specification 4



(d) Specification 6



Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 4. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable (in blue) is the climate transition risk proxy "carbon intensity" of the NACE 2 sector (as reported in the Fit-for-55 template) expressed in log and standardised, which is the weighted average of the ratios between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022 at the level of an activity sector. The second main independent variable (in orange) is the idiosyncratic part of carbon intensity, which is the different for each debtor between its own carbon intensity and the average of the sector. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

B.8 Analysis of the differentiated impact of climate transition risk and corporate loans interest rate depending on the level of uncertainty

Figure 13: Specification 3, minimum 2 banks ranking the same counterparty

(a) Independent variable:
Sectoral carbon intensity

(b) Independent variable:
Idiosyncratic carbon intensity

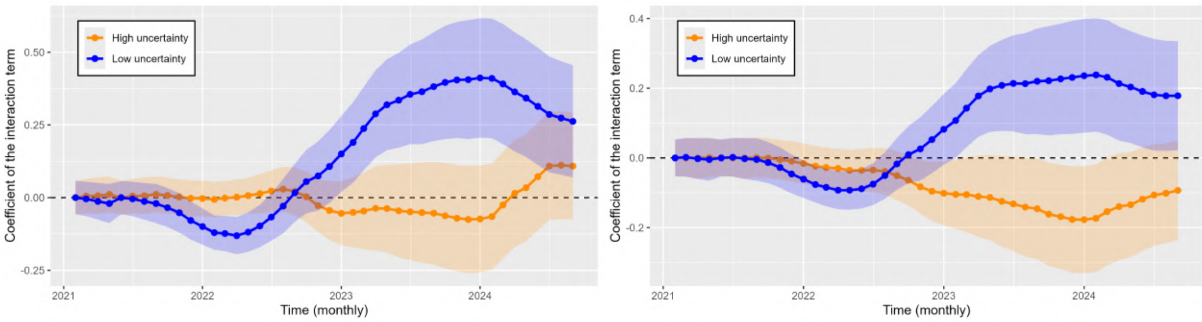
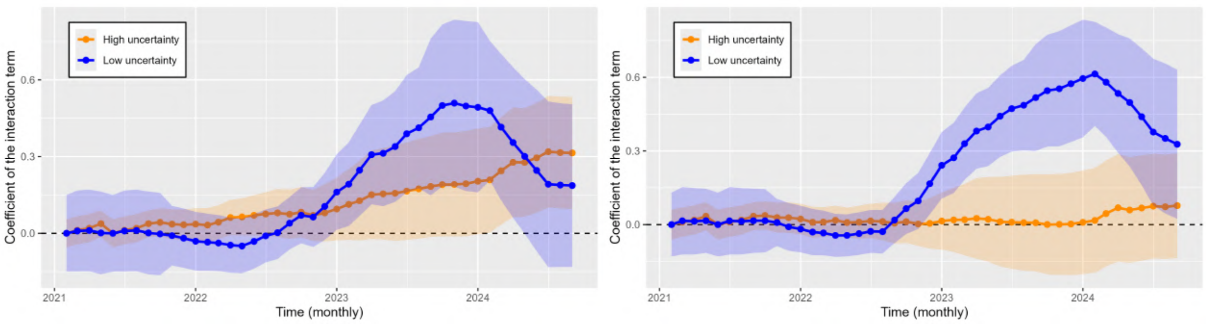


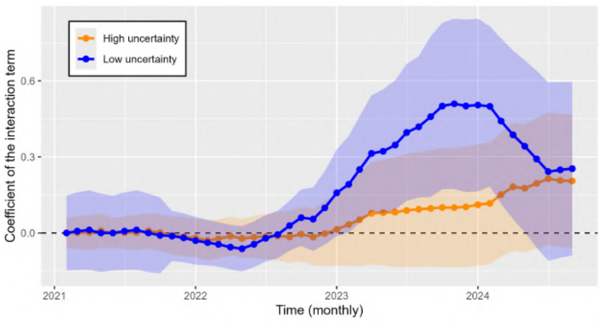
Figure 14: Specification 3, minimum 3 banks ranking the same counterparty



(a) Independent variable:
Sectoral carbon intensity

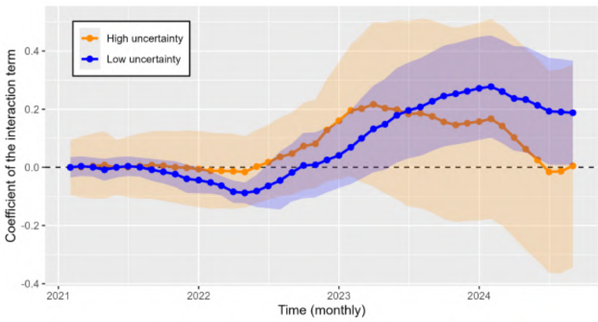
(b) Independent variable:
Idiosyncratic carbon intensity

Figure 15: Specification 4, minimum 3 banks ranking the same counterparty



(a) Independent variable:

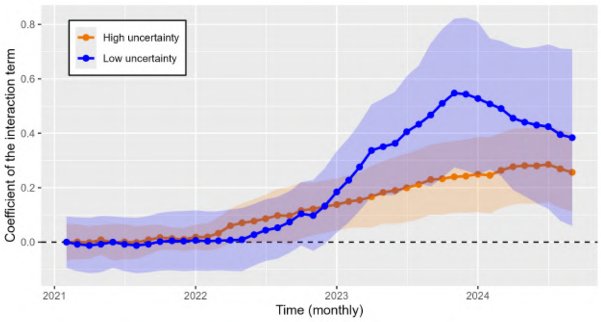
Sectoral carbon intensity



(b) Independent variable:

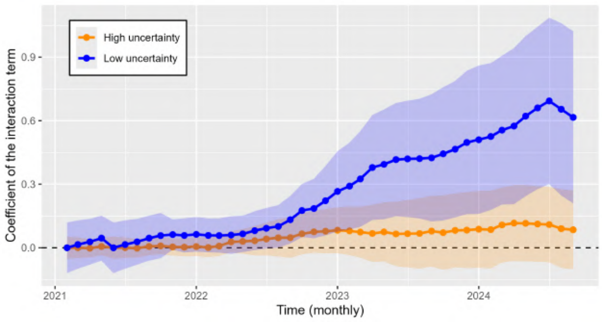
Idiosyncratic carbon intensity

Figure 16: Specification 6, minimum 3 banks ranking the same counterparty



(a) Independent variable:

Sectoral carbon intensity



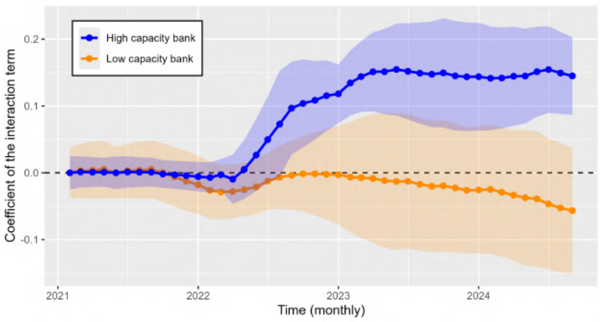
(b) Independent variable:

Idiosyncratic carbon intensity

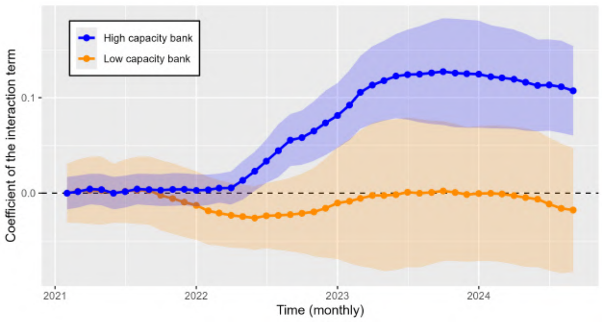
Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 4. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable (left panel) is the climate transition risk proxy "carbon intensity" of the NACE 2 sector (as reported in the Fit-for-55 template) expressed in log and standardised, which is the weighted average of the ratios between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022 at the level of an activity sector. The second main independent variable (right panel) is the idiosyncratic part of carbon intensity, which is the different for each debtor between its own carbon intensity and the average of the sector. The sample is splitted into two subgroups of firms in each panel based on carbon intensity uncertainty: the results for the 50% of firms with a carbon intensity uncertainty higher than the median are presented in orange while the results for the 50% of firms with a carbon intensity uncertainty lower than the median are presented in blue. The sample is also restricted to firms with at least two or three banks (depending the specification) that reported a carbon intensity value for the same firm. The specifications (3), (4) and (6) are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

B.9 Analysis of the differentiated impact of climate transition risk and corporate loans interest rate depending on the capacity of banks to determine which firms are green

Figure 17: Sample divided based on the number of flags received by banks during the first template submission (FDC1)

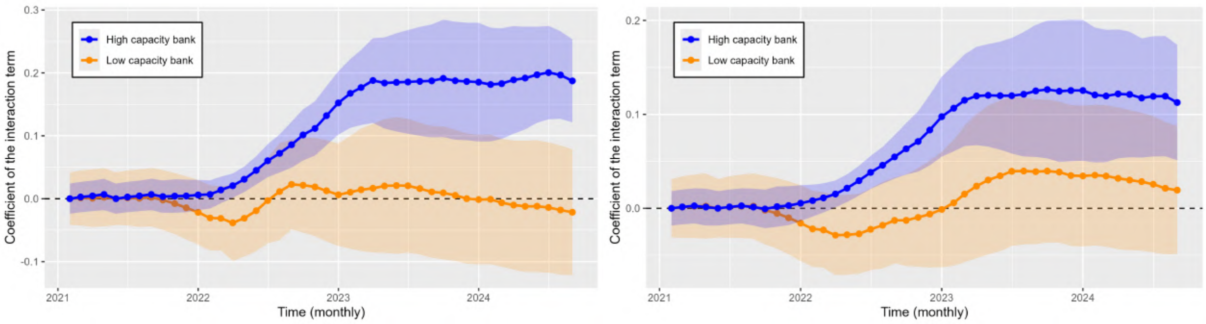


(a) Independent variable:
Sectoral carbon intensity



(b) Independent variable:
Idiosyncratic carbon intensity

Figure 18: Sample divided based on the number of flagsresolved between the first template submission (FDC1) and the last (FDC3)



(a) Independent variable: Sectoral carbon intensity

(b) Independent variable: Idiosyncratic carbon intensity

Note: These figures present the coefficient β_2 of the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 4. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable (left panel) is the climate transition risk proxy "carbon intensity" of the NACE 2 sector (as reported in the Fit-for-55 template) expressed in log and standardised, which is the weighted average of the ratios between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022 at the level of an activity sector. The second main independent variable (right panel) is the idiosyncratic part of carbon intensity, which is the different for each debtor between its own carbon intensity and the average of the sector. The sample is splitted into two subgroups of banks in each panel based on carbon intensity: the results for the 50% of banks with a number of flags received higher than the median are presented in orange ("low capacity bank") while the results for the 50% of banks with a carbon intensity lower than the median are presented in blue ("high capacity bank"). The sample is restricted to the 60 banks for which the number of flags received are observed. In the second specification, the banks are splitted based on the number of flags resolved between the first submission FDC1 and the last FDC3, an unresolved flags indicated an error done by the done that it was possible to resolve thus indicating clearly the fault of the bank. At the contrary, an unresolved flag can indicate a value impossible to obtain, independently of the capacity of the bank. The specifications (3), (4) and (6) are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. The confidence interval corresponds to a robust standard errors clustered at the bank-time level of 5% are presented in the charts.

Table 10: Decomposing capacity and greenness

	Interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon intensity:2022	−0.001	−0.045	−0.010	−0.020	0.002	−0.040
	(0.009)	(0.037)	(0.009)	(0.040)	(0.011)	(0.028)
Carbon intensity:2023	0.039	−0.080	0.029	−0.048	0.055*	−0.058
	(0.029)	(0.072)	(0.028)	(0.075)	(0.030)	(0.041)
Carbon intensity:2024	0.028	−0.091	0.013	−0.060	0.046	−0.085***
	(0.031)	(0.074)	(0.030)	(0.078)	(0.029)	(0.028)
Carbon intensity:capable bank	−0.058	−0.050			−0.034	−0.031
	(0.036)	(0.046)			(0.032)	(0.025)
Capable bank:2022	0.034	−0.271**	−0.044	−0.074		
	(0.122)	(0.112)	(0.125)	(0.116)		
Capable bank:2023	0.787***	−0.536	0.709**	−0.387		
	(0.249)	(0.765)	(0.276)	(0.778)		
Capable bank:2024	1.039***	−0.316	0.930***	−0.200		
	(0.221)	(0.829)	(0.259)	(0.843)		
Carbon intensity:capable bank:2022	0.049***	0.062	0.069***	0.030	0.042***	0.060*
	(0.015)	(0.041)	(0.017)	(0.044)	(0.014)	(0.030)
Carbon intensity:capable bank:2023	0.092**	0.154*	0.116**	0.131	0.059	0.100*
	(0.042)	(0.087)	(0.045)	(0.093)	(0.042)	(0.054)
Carbon intensity:capable bank:2024	0.088*	0.168*	0.117**	0.153	0.059	0.129**
	(0.045)	(0.090)	(0.050)	(0.098)	(0.044)	(0.049)
Probability of default	0.046	0.026	0.035	0.041	0.050*	−0.011
	(0.028)	(0.025)	(0.038)	(0.033)	(0.029)	(0.022)
Maturity	0.144***	0.160***	0.147***	0.171***	0.147***	0.133***
	(0.028)	(0.036)	(0.034)	(0.035)	(0.030)	(0.033)
Non-performing loan	−0.055	−0.067	−0.057	−0.038	−0.049	0.017
	(0.125)	(0.137)	(0.102)	(0.134)	(0.122)	(0.102)
Impairment ratio	0.023	0.048***	0.018	0.024***	0.040	0.027**
	(0.261)	(0.016)	(0.232)	(0.008)	(0.269)	(0.013)
Protection ratio	0.013	−0.059**	0.011	−0.091*	0.015	−0.057*
	(0.018)	(0.027)	(0.026)	(0.049)	(0.018)	(0.029)
Outstanding amount	−0.028	−0.039	0.132***	0.024	−0.036	−0.039
	(0.031)	(0.043)	(0.046)	(0.072)	(0.032)	(0.047)
Sample	Green banks	Brown banks	Green banks	Brown banks	Green banks	Brown banks
Firm Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank-Firm Fixed effects			*Yes*	*Yes*		
Bank-Time Fixed effects					*Yes*	*Yes*
Bank controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	59,340	27,840	59,340	27,840	59,340	27,840
R^2	0.687	0.737	0.804	0.823	0.746	0.817
Adjusted R^2	0.682	0.731	0.797	0.816	0.722	0.802

Note: This table reports the estimation results from the climate transition risk of debtors on interest rate, from OLS regressions as presented in Equation 2. The columns (1), (3) and (5) present the results for the subsample with brown banks as defined in Figure 11a (based on the percentile of the weighted average carbon intensity of banks), while columns (2), (4) and (6) present the results for the subsample of brown banks. The dependent variable is the weighted average interest rate that is individually agreed for the corporate loans between the reporting agent (banks are the creditors) b and the debtor (firm) f in month t. The main independent variable is the climate transition risk proxy "carbon intensity" expressed in log and standardised, which is the ratio between the Scope 1 greenhouse gas emissions of a debtor f and its total revenues at the end of 2022. The specifications are the same as presented in Table 6, except that the set of firm sector fixed effects is replaced by a set of firm fixed effects. The second independent variable of interest is "capable bank" defined according to the number of flags received during the first submission of the Fit-for-55 template as used in Figure 17. All variables are detailed in Section A.1. The estimation period starts in January 2021 and ends in September 2024. Robust standard errors clustered at the bank-time level are reported in parentheses below the respective coefficient estimate. *p<0.1; **p<0.05; ***p<0.01