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Climate transition risk and bank lending

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Abstract

We investigate whether and how banks in the global syndicated loan market adjusted the pricing and supply of credit to account for higher climate transition risk (CTR) in the years following the 2015 Paris Agreement. We measure CTR by considering the pollution levels of borrowers and the engagement of countries where borrowers are headquartered in addressing climate change issues. The evidence is mixed and points to nonlinear relations between lending variables and CO2 emissions. Policy events such as the Paris Agreement and government environmental awareness are significant climate risk drivers that, when combined, may amplify banks' perception of CTR.

JEL CLASSIFICATION

G2, Q3, Q5

1 | INTRODUCTION

Coping with climate risks, whether physical or transition-related, has become a priority for various stakeholders in the financial sector. Banks, particularly, play a unique role. Not only are they directly or indirectly exposed to climate risks, but they also hold a crucial position in the transition process. In fact, the success of the transition toward a greener economy depends on how effectively banks can channel credit towards low-emission borrowers and industries.

Yet, although potentially crucial, the role played by banks in the transition process remains unclear. First, while, in principle, higher risk would normally correlate with elevated funding costs for riskier firms, it remains uncertain whether banks would adjust their risk evaluation to incorporate climate and environmental risks in practice. This uncertainty is rooted in the challenge of quantifying climate change risk. Second, perceptions of climate change risk could intertwine with the credibility of climate policy implementation. Delays in enforcing climate policies and policy inconsistencies may impact how the materialization of climate-related financial risks is perceived. This can influence banks' risk assessment and, in turn, their propensity to invest in carbon-intensive firms. Additionally, the recent expansion of anti-environmental, social & governance (ESG) laws in certain US states, reported by Donefer (2023), suggests that bank investors and stakeholders might prioritize maximizing returns over environmental concerns. Furthermore, as De Haas and Popov (2019) find, financial markets may be more effective than banks in influencing the meeting of climate change-related goals. It follows that the banking system, rather than promoting, may actually slow the green transition, by preventing the financing of entry and innovation in industries most exposed to green technology externalities (Degryse et al. 2020). Hence, determining how banks react to higher climate risk remains an empirical question.

In this paper, we investigate whether and how banks adjust their lending policies in reaction to amplified climate change risk. Do they apply higher interest rates on riskier borrowers and industries? Do they curtail lending to these borrowers and industries?

To address these questions, we focus on climate transition risks (CTR), which pertain to the challenges associated with the adjustment process towards a low-carbon economy. This is important because the existing empirical analysis of how climate risk affects banks largely focuses on the effects of physical risks. In contrast, extant research on transition risks is more qualitative in nature and commonly centers around scenario analysis due to its forward-looking nature (see BIS 2021a and literature therein).

We collect firm-level CO2 emissions data, along with bank-firm data from the global loan syndication market, to measure bank exposures to large corporations across various industries and countries, showing broad cross-sectional heterogeneity between green and brown firms. We provide a comprehensive measure of exposure to climate transition risk that encompasses carbon emissions at both the borrower and industry levels, a macro-policy shock (i.e., the 21st Conference of the Parties or COP21, also known as the Paris Agreement), and an indicator of a country's commitment to engaging with climate change issues.

This approach enables us to account for multiple risk drivers and interactions that are inherent to climate transition risks. As argued (e.g., BIS 2021a), climate transition risks can stem from shifts in government policies, technological advancements, or changes in investor and consumer sentiment. Interestingly, economic sectors may have different sensitivities toward the transition to a low-carbon economy. Furthermore, climate change-related exposures diverge based on the geographic locations of both banks and their borrowers. Consequently, shifts in government policies and legislation, as well as changes in market dynamics and customer sentiments, emerge as significant climate risk drivers that could either exacerbate or alleviate transition risks. Consistently, in our setting, the impact of a firm's carbon emissions on bank lending can be either magnified or alleviated by climate risk drivers, such as the Paris Agreement, which marked a pivotal moment in raising global awareness of climate change. Additionally, a country's specific commitment to climate-related issues can make the same climate goals potentially more compelling and related actions more incisive in certain countries compared to others.

We obtain several findings. First, we document a positive association between CO2 emissions, loan prices, and loan supply over the entire time span considered. This suggests that banks were already conscious of their borrowers' environmental stance, as evidenced by the higher interest rates applied to larger emitters, even before COP21. Simultaneously, credit to these borrowers has increased as CO2 increased. Second, the direction of the relationships between loan variables and CO2 emissions reverse in the years following COP21, with both credit availability and loan prices decreasing as emissions increase. This indicates a shift in lending practices since the Paris Agreement, with banks granting less credit to larger emitters, but at a lower price. Third, the borrower's location plays a role in influencing banks' lending decisions by altering their perception of climate risk. Furthermore, the relationship between loan variables and climate risk is nonlinear and depends on both the climate vulnerability of the borrowers (proxied by the level of CO2 emissions) and the climate resilience of the government in the borrowers' home country (proxied by an index of environmental awareness and climate policy stringency). Specifically, we document a positive correlation between loan prices and borrowers' carbon emissions for highly vulnerable firms located in highly climate resilient countries after COP21. These firms receive, on average, larger loan amount, but a lower share of loans after the Paris Agreement, suggesting a reallocation effect. Finally, when we group borrowers by the industry level of carbon intensity, we find strong evidence of a price effect of increased transition risk. Borrowers from more polluting industries headquartered in climate resilient countries are charged higher prices following the Paris Agreement. At the same time, we document an increasing credit exposure to these more polluting industries, as both the amount and the share of loans allocated to them have increased.

The richness of our data allows us to investigate other relevant questions and exploit heterogeneity across banks, countries, and borrowers. We test whether banks in Europe, an area that is at the forefront of the fight against climate change, have reacted differently to increased CTR than banks located in jurisdictions less ambitious in copying with climate change, such as the US. Results do not show striking differences between European and US banks. Furthermore, we test whether banks identified as “green” display stronger effects in incorporating CTR in their lending decisions. Previous evidence is mixed. Kacperczyk and Peydró (2021) have shown that banks' commitment to climate related issues is important to steer credit allocation policies. On the other hand, Ehlers et al. (2022) have found no differences in loan pricing policies at banks with green attitude. Our findings do not support the hypothesis that banks labeled as “green” react to CTR differently than non-green banks. This points to banks' greenwashing and suggests that not all initiatives promoted as environmentally friendly are equally effective.

Overall, our results show that the Paris Agreement and government environmental awareness are significant climate risk drivers. When combined, these factors amplify banks' perception of CTR and, consequently, lead to shift in lending decisions. However, the bank strategy to cope with climate related risk is not straightforward. While we see a clearer effect on higher interest rates in response to higher climate change risk, the effects on credit supply are more ambiguous and depend on how borrowers' climate vulnerability is measured. If we measure vulnerability by the level of CO_2 emitted by the borrower, we document that banks have increased the amount but not the share of loans to larger emitters. Conversely, for borrowers grouped by industry pollution intensity, we find no evidence of reallocation, as banks increase both the amount and the share of resources provided to borrowers from highly polluting industries. These contrasting results point to the importance of relying on detailed data that capture the climate sensitivity of bank exposures at different levels.

This paper contributes to the extensive literature on climate risk and finance. Within this strand of literature, there is limited work analyzing climate risk drivers and their impact on banks. We fill this gap by examining how banks adjust their lending policies to higher transition risk and by accounting for various climate risk drivers at the levels of banks, borrowers, and countries.

Specifically, we extend the literature on the implications of climate change for banks, which is mainly focused on the loan pricing effects of climate-related risks (e.g., Degryse et al. 2023; Delis et al. 2021; Ehlers et al. 2022; Fard et al. 2020). Only a few studies examine how credit supply responds to increased climate-related risks (e.g., Kacperczyk and Peydró, 2021; Reghezza et al. 2021). Using loan-level data, Reghezza et al. (2021) document that bank lending to more polluting firms is reduced after the Paris Agreement. Kacperczyk and Peydró (2021) employ bank-level commitments to decarbonization as a proxy for changes in banks' green preferences and, through these commitments, shocks to firms with previous credit from these banks. They find that firms with a higher carbon footprint, previously borrowing from committed banks, subsequently receive less bank credit. Unlike these contributions, we consider both the loan price and credit supply effects of increased climate risk. Our results suggest that banks respond to increased climate risk in a non-univocal manner.

Another contribution to the understanding of the implications of climate-related risks for banks lies in the richness of our data set. Bolton et al. (2020) underscore that using country-level measures alone would be misleading, as country-level variation could be influenced by factors other than carbon transition. Going beyond industry-level analysis is also crucial because each bank faces “idiosyncratic climate-related financial risks within its portfolio, based on the geographies, sectors, political environment, and technological frontiers to which its clients and counterparties are exposed” (BIS 2021b). Additionally, employing firm-level data for carbon emission measurement aligns with CTR definitions adopted by financial authorities in their climate stress test exercises, as Baudino and Svornos (2021) note.

Moreover, using bank-borrower data from the syndicated loan market is relevant for alleviating the identification challenge of disentangling credit demand from supply. We can control not only for bank-specific factors but also for firm-specific characteristics that can influence bank loan pricing and amounts. Additionally, larger emitters tend to be large-sized companies financed through big-ticket funding as syndicated loans. Finally, the syndicated loan market provides an ideal setting for investigating banking behavior in the context of CTR due to the unique aspects of syndicated deals, including the lead arrangers' incentives and responsibilities toward other members of the syndicate (Ivashina 2009).

The rest of the paper is organized as follows. Section 2 illustrates the institutional framework by discussing how climate change-related risks may impact banks and by focusing on the measurement of climate transition risk. It also reviews the existing literature and outlines the testable predictions. Section 3 explains data and methodology. Section 4 comments on the results. Section 5 concludes.

2 | INSTITUTIONAL FRAMEWORK

2.1 | Climate change-related risks and transmission channels on bank balance sheets

Banks are susceptible to climate change impacts through macro- and microeconomic transmission channels stemming from two distinct types of climate risk drivers (see, e.g., BIS 2021a; Bolton et al. 2020). Firstly, they might incur economic costs and financial losses due to the escalating severity and frequency of physical climate risk drivers. Secondly, as economies strive to curtail carbon dioxide emissions, which constitute the majority of greenhouse gas (GHG) emissions, these efforts give rise to transition risk drivers, such as shifts in government policies, technological advancements, and shifts in investor and consumer sentiment. In both scenarios, increased climate risk can manifest directly through banks' exposures to borrowers and countries facing climate-related shocks, or indirectly through the repercussions of climate change on the broader economy and the feedback effects within the financial system. These exposures become evident through amplified default risks in loan portfolios or decreased values of assets. Consequently, the impacts of these risk drivers on banks can be observed through "traditional" risk categories, including credit risk.

For example (see Reghezza et al. 2021, among others), extreme weather events may have negative effects on properties, agricultural productivity, human labor and physical assets, thus impairing firm profitability and balance sheets. This "physical" channel is likely to translate into higher credit risk for banks as damages to borrowers'activities may entail lower creditworthiness and higher default probability. A possible repercussion of transition risk, on the other hand, could be a repricing of bank asset values. This could lead to fire sales of carbon-intensive assets, potentially causing liquidity problems for banks heavily exposed to climate-sensitive sectors. Another consequence involves higher market risk due to increased uncertainty and procyclicality. Additionally, unforseen changes might spur technological shocks and/or changes in consumers' behavior, potentially reducing the profitability of carbon-intensive firms. In turn, this could lead to higher credit risk for most exposed banks.

Although intertwined, climate-related risks differ from conventional financial risks in many peculiar aspects (Carney 2021). They occur unexpectedly in terms of both timing and magnitude; thus, past data provide little help when forecasting future evolution. In addition, these events are likely to impact entities across sectors and countries, in a correlated, nonlinear, and irreversible manner. In addition, while physical risks are long-term, action to cope with them has to be taken "now" to have an impact: this is referred to as the *"tragedy of the horizon"* (Carney 2015). For all these reasons, climate change represents a systemic risk affecting the whole real economy and the financial system alike.

2.2 | Measures of exposure to climate transition risks and the Paris agreement

A relevant topic in the discussion on the impact of climate change in banking deals with the issue of how to measure bank and borrower exposure to climate risks. Relatedly, developing proper climate-specific risk management tools for banks is difficult and cumbersome (BIS 2021b; FSB 2020 and 2021; NGFS 2019).

As far as transition risk is concerned, a commonly used measure among academics, supervisors and banks is the amount of CO2 emissions (ECB 2021a and 2021b). The underlying idea is that more polluting firms are more likely to be targeted by climate regulation, which may entail costs and losses for banks triggered by the mechanisms described in the previous section. Another common proxy for CTR is the stringency of climate policies in a given country (e.g., Benincasa et al. 2021; Delis et al. 2021). If climate change mitigation is a priority in the national political agenda, it is more likely that companies will have to face rules and fines, or to sustain unplanned investments in greener technology to adapt to the new framework.

Another way to measure CTR is also by looking at significant events that either have introduced limits to activities of companies, countries and investors (see Fard et al. 2020 who exploited the introduction of the 2005 European Trading Scheme) or have changed people's, policy makers' and institutions' perception of environmental matters. In this last respect, an event commonly regarded as a major spark of climate transition risk is the document ratified at the closing of the 21st Conference of the Parties (COP21) on December 12th, 2015, also known as Paris Agreement (e.g., Delis et al. 2021; Reghezza et al. 2021). The Agreement, which brought together 194 Parties, set out a global framework to avoid dangerous climate change, in the ambitious attempt to reach climate-neutrality before the end of the century. The best-known resolution of the Agreement is the one related to mitigation policies, meaning actions concerning the reduction of GHG emissions to limit global warning. To achieve this goal, countries have agreed to review their own commitments every 5 years, as well as to provide financing to developing countries to mitigate climate change and strengthen resilience to adapt to climate impact. With its entry into force on November 4th, 2016, the Paris Agreement became a legally binding international treaty, the first-ever universal and legally binding climate change agreement on a global basis. By stating the need to "make finance flows compatible with a pathway toward a low greenhouse gas emissions and climate-resilient development", it also represents the first climate deal that explicitly recognizes the role of the financial system on environmental actions.

Literature on transition risks has often identified the months around the Paris Agreement (COP21) as a period of increased salience of CTR, resulting in banks shifting their prevailing perception of those risks (e.g., Mueller and Sfrappini 2022; Bolton and Kacperczyk 2023). For instance, Delis et al. (2021) look at the relation between climate policy exposure (quantified by a proxy for the amount of stranded assets of a fossil fuel firm in a given year) and syndicated loan spreads for fossil fuel firms, finding higher loan spreads to fossil fuel firms after 2015. Ehlers et al. (2022) investigate the relation between firm-level CO2 emissions in the oil and gas sectors and syndicated loan margins and find evidence of a statistically significant carbon premium, which increased after the Paris Agreement. The effect is driven by the so called Scope 1 carbon emissions rather than the broader carbon footprint of a firm. Reghezza et al. (2021) investigate whether euro area (EA) banks changed their bank lending behavior following the COP21. They find that EA banks reallocated credit away from polluting companies, by reducing the loan share for polluting firms compared with that for less polluting firms.

As for other relevant events in the debate on climate change, Ivanov et al. (2023) consider the periods between the announcement and the approval (or rejection) of the California Cap-and-Trade Bill and the federal Waxman-Markey Cap-and-Trade Bill as times in which uncertainty related to CTR was particularly pronounced. They uncover that corporate lending adjusts quickly when transition risks are high. Finally, Antoniou et al. (2020) exploit the implementation of phase III of the EU Emission Trading System and find that, despite the program was designed to pass the cost of CO2 emissions to the polluters, since 2013, loan spreads charged to those borrowers fell by almost 25%.

2.3 | Main related literature and testable predictions

We investigate banks' reaction to climate-related transition risks by looking at two dimensions of bank lending behaviour: loan pricing and credit supply.

First, we aim to understand whether and how banks incorporate CTR into loan pricing, and whether any changes occurred since the 2015 Paris Agreement (**RQ1**). Second, we aim to explore bank lending practices toward more exposed borrowers as a result of increased CTR concerns, i.e., in the years following the Paris Agreement (**RQ1**).

Previous findings show that banks tend to price risks related to policy changes induced by climate issues. Bolton and Kacperczyk (2023) document that financial markets price climate transition risks, although the impact of the Paris Agreement is not uniform across countries. Degryse et al. (2023) find that borrowers who are more transparent in disclosing their carbon emissions and emit fewer pollutants receive more favorable lending terms. Ehlers et al. (2022) uncover that after the signing of the Paris Agreement, banks charged higher loan rates to companies with higher carbon emissions as a share of their revenues.

Given this previous evidence, we anticipate that larger carbon emitters will face higher loan spreads. We also expect this effect to be more pronounced after the signing of the Paris Agreement and in countries that are more sensitive to climate change issues.

In contrast, the existing evidence on how banks adjust credit supply as a consequence of increased climate risk is mixed. The literature on the risks of assets becoming stranded (such as fossil fuel reserves, if environmental regulations substantially limit access to them) warns about the possibility that firms highly exposed to climate policy and transition risks may need to find alternative sources of financing. Empirical findings from the tobacco industry by Hong and Kacperczyk (2009) suggest that higher perceived risk may lead to higher risk premiums required by equity investors, potentially prompting vulnerable firms to seek other funding sources. Similarly, Delis et al. (2021) find that fossil fuel companies would need to increase their credit volume to compensate for "lost access to equity finance". Conversely, other studies show a bank credit reallocation effect from brown to green firms following banks' specific commitments, as Kacperczyk and Peydró (2021), or policy shocks (for instance, Reghezza et al. (2021) exploit the signing of the Paris Agreement, Ivanov et al. (2023) the introduction of the California Cap-and-Trade Regulation). Additional studies, such as Mueller and Sfrappini (2022), hint at different bank behaviors towards European versus US firms.

Based on this evidence, two opposite reactions to increased CTR are plausible. On one hand, the persuasive effects of the Paris Agreement could incentivize lenders to reduce credit to more polluting firms due to concerns about possible (direct or indirect) consequences of transition risks. On the other hand, banks may be encouraged to lend even more to more polluting firms after COP21 while, in the absence of binding constraints, they are still allowed to do so. In contrast, one may expect the persuasive effects of the Agreement to be more intense in countries that are more aware of climate change issues. Whether banks will grant more or less credit to more polluting borrowers remains, a priori, unclear and needs to be tested empirically.

3 | DATA AND METHODOLOGY

3.1 | Data and summary statistics

3.1.1 | Sources of data

This study relies on multiple sources of data. We retrieve data on syndicated loans from Thomson Reuters DealScan, which provides the most comprehensive loan-deal information on a global level. The unit of observation is the loan (or facility), which is usually grouped into deals or packages. We collect data on bank loans including details on the lender (name and loan share), the loan (maturity, amount, origination date, presence of collateral and covenants), and the borrower (name and location).

As far as climate transition-related risks are concerned, we employ several direct and indirect proxies of CTR to account for both firms' individual vulnerability to transition risk and the degree of engagement in dealing with climate-related issues in the country in which borrowers are located.

We measure firm-level pollution in terms of carbon emissions. Unlike studies that employ ESG ratings, we use an absolute measure of pollution, i.e., the total CO2 emissions (in thousands of tonnes), retrieved from Thomson Reuters Eikon. There are a few reasons suggesting that total CO2 are preferable measures of a firm's exposure to climate change risk. First, ESG ratings are questionable indicators of exposure to climate risk due to discrepancies across different providers, frequent updates, and systematic measurement errors (see, for instance, Berg et al. 2022, Chatterji et al. 2016).[1] Second, as argued by Ehlers et al. (2022), the usage of total emissions (over the different Scope measures) mitigates the concern of greenwashing and pollution outsourcing by companies. This is because relying mainly on Scope-1 carbon emissions (i.e., those deriving from owned or controlled sources) may disregard the fact that firms can maintain their (presumably high) carbon footprint while, at the same time, outsourcing carbon intensive activities to reduce their Scope-1 emissions in countries with stricter environmental policies (Ben-David et al. 2021).

To capture information on country-level engagement in climate-related issues, we resort to Germanwatch's Climate Change Performance Index (CCPI), which tracks countries' efforts to combat climate change. This indicator is considered a long-standing and reliable tool for identifying leaders and laggards in climate protection (see, e.g., Delis et al. 2021). The CCPI, which is published annually, is constructed as a 0-100 indicator, where the country's commitment to environmental goals increases with the score.[2] The overall indicator is calculated from the weighted sum of four components: per capita GHG emissions (40% weighting), Renewable Energy (20% weighting), Energy Use (20% weighting), Climate Policy (20% weighting), totalling 14 indicators. The rationale behind choosing these four components is that effective Climate Policy will influence Energy Use and Renewable Energy over a few years, ultimately reducing GHG Emissions.

To identify vulnerability to rising CTR, we focus on the rightmost part of the CO2 emissions and of the CCPI distributions. We define firms as "Vulnerable" to transition risks if their CO2 emissions exceed specific percentiles in a given year. In line with recently-introduced climate stress tests,[3] we consider the 50th and the 75th percentiles of the distribution as relevant thresholds. Similarly, to assess a country's climate resilience, we classify countries as "High CCPI" if their score is above the 50th and the 75th percentiles of the CCPI distribution in a given year.

Lastly, to account for the increased salience of CTR, we introduce interactions between borrower climate vulnerability, borrower's country climate resilience, and the dummy post Paris Agreement, which constitutes the third prong of our CTR proxy. This is relevant because the Paris Agreement increased worldwide commitment to climate change mitigation actions, leading to a shift in banks' perception of climate-related risks.

Table 1 reports the definitions of all the variables used in our analysis.

3.1.2 | Sample selection and characteristics

The original DealScan sample consists of a cross-section of syndicated loan tranches originated from 2010 to 2021 to borrowers located worldwide, resulting in 510,682 observations. All amounts are converted to USD. Consistent

[1]Examples of works that have documented an association between ESG ratings and loan pricing include Sharfman and Fernando (2008); Goss and Roberts (2011); Hauptmann (2017); Erragragui (2018); Houston and Shan (2022). These works deal with corporate social responsibility in general, and not with climate transition risk which is better captured by more specific indicators.

[2]Germanwatch provides measures for 57 countries and the EU. Data are accessible at https://www.germanwatch.org/en/CCPI.

[3]E.g., the ECB's 2021 economy-wide climate stress test (see Alogoskoufis et al. 2021).

TABLE 1 Variable definitions.

Variable	Description	Source
Dependent variables		
Margin	Loan margin in bps	*DealScan*
LoanAmount	Amount of issued loan in thousand USD (taken as a logarithm)	*DealScan*
LoanShare	Amount granted through syndicated lending by a given bank to a specific borrower in a year as a share of the bank's gross loans in the year	*DealScan, Bank Focus, own calculations*
Independent variables		
CO2Emissions	Total CO2 and CO2 equivalents emissions in thousand tonnes	*Eikon*
CCPI	Climate Change Policy Index of country *c* in year *t*	*Germanwatch*
Loan-level controls		
Maturity	Maturity of the facility, in months	*DealScan*
nLeaders	Number of leaders in the facility	*DealScan, own calculations based on the definitionprovided by* Ivashina (2009)
Secured	Dummy equal to 1 if the loan is collateralized	*DealScan*
Covenants	Dummy equal to 1 if the loan has covenants	*DealScan*
PerfPricing	Dummy equal to 1 if the loan has performance pricing	*DealScan*
Borrower-level controls		
FirmSize	Logarithm of total assets the borrowing firm (in million USD)	*Orbis*
FirmLeverage	Leverage of the borrowing firm	*Orbis*
FirmProfitability	ROA of the borrowing firm	*Orbis*
Industry	Industrial sector of the borrowing firm, SIC 2-digits classification	*DealScan*
Lender-level controls		
BankSize	Logarithm of total assets of the bank (in thousands USD)	*Bank Focus*
BankE/TA	Equity to total assets of the bank	*Bank Focus*
BankProfitability	ROA of the bank	*Bank Focus*
Country-level controls		
GDP growth	GDP growth of country c in year t, in %	*World Bank*
Δ Monetary rate	Annual variation in monetary policy rates (annualized)	*International Monetary Fund*

with previous studies, we consider only entries for which information on loan rates (defined either by margin or all-in-spread drawn) is available.[4] We classify as "lenders" institutions categorized as Commercial Banks, Finance Companies, Investment banks, Mortgage Banks, Thrift/S&L, and Trust Companies in DealScan. We include only

[4]In cleaning the syndicated loan data set we follow, in particular, Ivashina (2005) and (2009), Benincasa et al. (2021); Doerr and Schaz (2021); Ehlers et al. (2022).

lead banks in each syndicate, as they are informed agents with strong monitoring incentives.[5] Furthermore, we only include loans to nonfinancial firms (excluding borrowers with SIC code between 6000 and 6999).

We then match the refined sample extracted from DealScan with data from various sources to create a rich and comprehensive data set encompassing financial, economic and environmental characteristics at the loan, borrower, lender, and country levels. Specifically, using the borrower ISIN numbers, we match DealScan entries with Eikon climate risk measures, including firm-level carbon emissions and ESG scores. Borrower information from DealScan is also matched with BvD Orbis' corporate database, and lender data with BvD Bank Focus. Additionally, we collect bank-level data on the signing of the green principles of the United Nations Environment Programme Finance Initiative (UNEP-FI), which is used in the extensions to the main analysis.[6] Finally, we retrieve country-level data on annual GDP and annual GDP growth from the World Bank's WDI database, as well as monetary rates from the IMF.

After data cleaning and matching, the sample comprises 48,825 records. The final sample, limited to deals issued up to 2018, includes 8,488 observations, each uniquely identified by facility and lender. These observations correspond to 1,951 unique deals granted by 185 distinct lenders to 556 unique borrowers headquartered in 33 countries (Table A1, Panel A). The borrowing firms operate in 56 2-digit SIC industries, corresponding to 11 industrial sectors (Table A1, Panel B). As expected, most syndicated loans are granted to firms in the US market.

The data are aggregated at two levels. As in Degryse et al. (2020), the Facility-Lead arranger sample is obtained by associating each lead bank with the corresponding facility, treating the facility-leader pairing as the unit of observation.[7] This approach allows us to better control for more granular individual bank time-varying and time-invariant characteristics. This allows for unobserved cross-sectional differences among lenders, as we examine the loan spreads across firms with different pollution levels within the same bank. A second level of aggregation refers to the Lender-Borrower dimension. This enables us to construct *LoanShare*, a measure representing the weight of total credit granted through loan syndication by a given bank to a specific borrower in a fiscal year, relative to the bank's total loans recorded for that year.[8] Considering the share of loan to polluting firms aligns with the proposal to use the loan book exposures to carbon-intensive sectors or firms as a proxy of transition risk faced by banks (ESRB 2020).

Table 2 shows summary statistics for the Facility-Lead Arranger and the Lender-Borrower samples. Considering the Facility-Lead Arranger aggregation (Panel A), the average number of lead banks per loan is 7.89. The average loan facility has a cost (margin) of nearly 144 basis points,[9] a maturity of slightly more than 4 years (51.84 months), and an amount of 2.03 million dollars. As for the Lender-Borrower data set (Panel B), on average, the annual amount of credit granted via syndicated loans by bank *b* to firm *f* is 8% of bank *b*'s gross loans and 11% of total syndicated loans issued by the same bank *b* during the year. Employing two different configurations give rise to discrepancies in the number of observations and, more generally, in summary statistics. Within the Facility-Lead Arranger data set, borrowing firms receiving syndicated loans characterized by a larger pool of lead banks are included in more records as opposed to companies borrowing from syndicates with a smaller number of leaders.[10] Likewise, in the Lender-Borrower configuration, borrowing firms which engaged in deals with different lead banks in the same fiscal year are implicitely given more weight compared to borrowers that were granted loans by the same lender. Moreover, in the Lender-Borrower data set, discrepancies may arise due to data availability problems, related to the

[5]As in Ivashina (2009) the lead bank is first identified with the administrative agent, i.e., the bank that conducts due diligence, handles all the payments, and monitors the loan. If not available, the lender acting as agent, arranger, bookrunner, lead arranger, lead bank, or lead manager is defined to be the lead bank.

[6]The list of signatories as well as the date of their joining can be accessed at https://www.unepfi.org/members/.

[7]If facility *l* were granted to borrowing firm *f* by a pool of two lead banks (bank *i* and bank *j*, the data set would record two entries: one for the couple facility *l* to borrower *f* – bank *i*, and one for the facility *l* to borrower *f* – bank *i*.

[8]The measure is computed dividing the total amount of (syndicated) lending granted by bank *i* to firm *j* in year *t* (obtained by multiplying lender share by loan facility amount, as derived from DealScan) by bank *i*'s gross loans in year *t*, as retrieved from Bank Focus. Both loan amount and gross loan measures are in thousand dollars.

[9]To account for the presence of spurious outliers, loan margin is right-winsorized by year at the 1% level.

[10]Facilities with high syndicate concentration get, by construction, more weight compared to those with smaller pools of lead banks since loan facilities with x amount of lead arrangers are duplicated x number of times in the data.

TABLE 2 Summary statistics.

Variables	N	Mean	SD	Min	p25	p50	p75	Max
Panel A: Facility-Lead Arranger data set								
Loan margin (bps)	5082	143.59	96.98	1.00	75.00	120.00	190.00	600.00
Loan amount (log)	5082	6.71	1.40	−0.45	5.89	6.82	7.60	10.59
Loan amount (thousand USD)	5082	2028.93	3993.81	0.64	360.00	914.94	2000.00	39900.00
nLenders	5082	7.89	7.22	1.00	1.00	6.00	12.00	31.00
Secured	5082	0.15	0.36	0.00	0.00	0.00	0.00	1.00
Maturity (months)	5082	51.84	23.67	1.00	37.00	60.00	60.00	725.00
Performance Pricing	5082	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Covenants	5082	0.25	0.43	0.00	0.00	0.00	1.00	1.00
Bank's ROA	3538	0.53	0.61	−15.80	0.23	0.45	0.88	4.91
Bank's E/TA	3694	6.94	3.63	1.08	4.75	6.00	9.04	67.39
Bank's total assets (log)	3689	13.24	1.61	5.47	12.64	13.83	14.37	15.21
Bank's total assets (thousand USD)	3689	1087553	821351	236	310000	1015625	1747354	4041959
Bank's Tier1 ratio	3234	13.06	3.09	0.00	11.50	12.80	14.17	64.63
Bank's Cost-to-Income Ratio	3536	62.44	16.03	5.38	52.56	60.59	71.16	315.96
Bank's NLP to Total Loans	3346	2.72	2.69	0.00	1.00	1.83	3.40	42.87
GreenBank (UNEPFI)	5082	0.43	0.49	0.00	0.00	0.00	1.00	1.00
Firm's total assets (log)	4313	9.64	1.41	5.57	8.69	9.63	10.62	13.00
Firm's total assets (thousand USD)	4331	37774	56443	0.00	5819	15228	40879	444097
Firm's leverage	4448	0.42	0.17	0.00	0.31	0.41	0.53	1.11
Firm's ROA	4456	4.32	8.47	−82.62	1.80	3.49	6.65	59.70
Firm's sales (log)	4284	9.14	1.41	4.83	8.28	9.12	10.33	13.09
Firm's sales	4284	22469.22	36263.84	124.73	3926.89	9093.09	30561.85	485873.00
Firm's CO2 Emissions (thousand tonnes)	5082	9731.11	27053.94	0.15	175.76	1004.55	5180.00	232011.70
Firm's CO2/Revenue (tonnes/ million USD)	5082	548.38	1657.89	0.32	24.11	94.92	515.04	24748.65
Firm's country CCPI (0-100)	5082	54.17	11.89	25.03	48.50	54.91	64.60	74.32
Vulnerable (top25)	5082	0.28	0.45	0.00	0.00	0.00	1.00	1.00
Vulnerable (top50)	5082	0.54	0.50	0.00	0.00	1.00	1.00	1.00
High CCPI (top50)	5082	0.47	0.50	0.00	0.00	0.00	1.00	1.00

TABLE 2 (Continued)

Variables	N	Mean	SD	Min	p25	p50	p75	Max
High CCPI (top25)	5082	0.32	0.47	0.00	0.00	0.00	1.00	1.00
GDP growth	5082	2.29	2.42	−7.09	1.55	2.26	2.87	25.18
Δ Monetary policy rate	4267	0.15	0.78	−3.78	−0.26	0	0.67	2.81
Panel B: Lender-Borrower data set								
Loan Share (% Gross Loans)	4662	7.91	11.90	0.16	1.45	3.27	8.52	66.84
Loan Share (% Syndicated Loans)	4662	0.11	0.20	0.00	0.02	0.04	0.11	1.00
(Avg.) Maturity	4662	51.02	12.43	12.00	45.63	54.26	60.00	124.62
(Avg.) Margin	4662	130.15	53.76	17.50	96.76	126.22	155.17	451.25
Bank's ROA	4436	0.67	0.86	−15.80	0.33	0.67	1.00	33.63
Bank's E/TA	4528	7.98	3.56	−2.11	5.36	7.24	10.42	96.39
Bank's total assets (log)	4662	13.05	1.40	7.99	11.82	13.41	14.29	15.21
Bank's total assets	4662	919983.10	842336.80	2954.18	135758.40	668174.40	1601782.00	4041958.00
Bank's Tier1 ratio	4360	12.65	2.36	0.00	11.27	12.48	13.57	42.47
Bank's Cost-to-Income Ratio	4611	60.47	14.72	12.54	52.21	58.99	69.06	277.76
GreenBank (UNEPFI)	4662	0.37	0.48	0.00	0.00	0.00	1.00	1.00
Firm's country GDP growth	4662	2.32	1.16	−7.09	1.84	2.33	2.99	8.26
Firm's leverage	4662	0.44	0.18	0.05	0.32	0.44	0.57	1.80
Firm's ROA	4662	4.10	7.71	−57.66	2.02	3.85	7.31	32.59
Firm's total assets (log)	4662	9.98	1.26	6.24	9.16	9.85	10.85	12.91
Firm's total assets	4662	47005.52	67827.19	514.75	9526.20	19010.00	51653.00	403821.00
CO2 Emissions (thousand tonnes)	4662	8947.63	22470.26	0.15	362.97	1658.92	6272.00	232011.70
CO2/Revenue	4662	610.66	1603.91	0.46	29.22	80.06	472.50	17148.46
Firm's country CCPI	4662	50.41	9.53	25.03	48.50	52.33	54.91	74.32
Vulnerable (top25)	4662	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Vulnerable (top50)	4662	0.59	0.49	0.00	0.00	1.00	1.00	1.00
High CCPI (top50)	4603	0.13	0.34	0.00	0.00	0.00	0.00	1.00
High CCPI (top25)	4603	0.07	0.26	0.00	0.00	0.00	0.00	1.00
GDP growth	4662	2.32	1.16	−7.09	1.84	2.33	2.99	8.26
Δ Monetary policy rate	3912	0.16	0.84	−2	−0.3	0	0.67	2.81

fact that the construction of the dependent variable *LoanShare* requires information on both the lender's share within the syndicate (source: DealScan) and that lender's total loans (source: Bank Focus).

3.1.3 | Trends in bank lending and CO2 emissions in the pre-post Paris Agreement

To investigate the relationship between firms' carbon emissions and bank lending, especially considering the Paris Agreement, Table 3 presents a t-test comparing differences in means of the loan-level variable of interest computed before and after COP-21, for each decile of the CO2 emissions distribution. Overall, the average loan margin offered to firms in the central deciles (3rd–7th) has significantly declined over the sample period, as has that for the top decile. In contrast, the average price charged to the least polluting firms (those in the bottom decile) has increased by 32 basis points. Regarding credit volume, the t-test exercise highlights a general increase in the post-period in the average amount of syndicated loans issued to firms in the first seven deciles of the CO2 emissions distribution. This increase is also reflected in the weight of syndicated lending relative to banks' gross loans (see the panel on Loan Share). On the other hand, firms in the top 20% of the CO2 emissions distribution experienced, on average, a reduction in loan amount and the corresponding share of total gross loans, suggesting a reallocation of credit towards less polluting firms (i.e. borrowers in the 6th and 7th deciles).

This preliminary test suggests that, in the pre-post Paris Agreement period, overall banks have granted less credit to the more polluting firms while simoultanesly reducing the cost of credit. However, lending practices to more polluting firms may have changed for reasons unrelated to CO2 emission considerations and could be influences, for example, by firm-specific factors. To gain further insights into our sample composition, Table A2 in the Appendix shows the results of the t-test comparing differences in means of several characteristics between Vulnerable and Non-Vulnerable firms, i.e., those with CO2 emission levels above/below the 50th percentile threshold.

For example, Panel A in Table A2 underscores that vulnerable borrowers, on average, display a lower loan margin and maturity, a higher loan amount, and, consequently, are engaged in deals characterised by a higher number of lead banks. Additionally, companies included in the Vulnerable group are, on average, larger, more leveraged, and less profitable compared to those in the Non-Vulnerable group. These differences may be influenced by industry-specific factors: borrowers labeled as Vulnerable are concentrated in a narrower range of industries, predominantly in mining, transportation, communication, and utilities sectors. Fossil fuel firms, in particular, tend to be large and highly leveraged companies, making them more likely to seek funds in the syndicated loan market (Delis et al. 2021).

The characteristics of lenders between the two groups are comparable. Although lenders to non-vulnerable borrowers appear to be better capitalised and smaller than lenders to vulnerable borrowers, the economic relevance of these differences is negligible. Similarly, disparities between borrower country-level variables (CCPI and GDP growth) are small, if not negligible. Similar considerations apply to the Lender-Borrower data set (Table A2, Panel B).

Overall, the descriptive statistics show there is great heterogeneity in our sample that is worth exploring. This calls for a multivariate analysis to investigate the role of CTR on loan pricing and supply, considering the characteristics of loan facilities, lenders, and borrowers.

3.2 | Methodology

To investigate the impact of exposure to CTR on loan pricing (**RQ1**), we refer to the Facility-Lead data set. In line with previous literature (for instance, Delis et al. 2021, Ehlers et al. 2022, Fatica et al. 2021) we adopt the following the specification:

TABLE 3 t-tests for differences in means of loan characteristics before and after the Paris Agreement, by CO2 emissions decile.

CO2 emissions deciles	Pre-Paris Mean	Pre-Paris SD	Post-Paris Mean	Post-Paris SD	t-test Difference	t-test S.E.
Loan margin (bps)						
1st Decile	162.213	91.239	194.629	87.955	32.416***	(4.059)
2nd Decile	138.592	86.453	149.381	73.164	10.789	(1.488)
3rd Decile	173.03	102.452	125.732	72.704	−47.298***	(−6.08)
4th Decile	109.936	55.002	157.085	115.387	47.149***	(5.450)
5th Decile	202.143	135.958	159.858	115.48	−42.285***	(−3.769)
6th Decile	192.067	109.182	130.81	83.46	−61.257***	(−7.158)
7th Decile	134.374	82.328	97.718	75.349	−36.656***	(−4.926)
8th Decile	98.101	79.771	105.026	77.805	6.924	(0.917)
9th Decile	138.063	100.13	139.4	48.912	1.337	(0.201)
10th Decile	133.746	96.43	102.311	89.55	−31.435***	(−3.392)
Loan amount (thousand USD)						
1st Decile	541.445	559.709	653.407	618.318	111.962*	(2.108)
2nd Decile	493.161	485.853	4770.119	8475.442	4276.957***	(8.442)
3rd Decile	788.984	737.768	2145.725	2376.625	1356.741***	(7.654)
4th Decile	1057.194	1297.899	2093.649	2727.854	1036.455***	(5.069)
5th Decile	1134.408	1071.437	1399.584	1851.814	265.176	(1.884)
6th Decile	1185.275	1276.92	1669.554	1900.151	484.280***	(3.464)
7th Decile	1623.292	1376.045	2222.55	1908.612	599.258***	(3.576)
8th Decile	4438.418	6575.456	5186.439	12278.95	748.02	(0.715)
9th Decile	1969.003	1923.858	1204.823	1583.88	−764.181***	(−4.608)
10th Decile	3456.407	2745.913	2358.245	3006.68	−1098.162***	(−3.684)
Loan Share (%)						
1st Decile	4.224	5.825	4.923	7.526	0.699	(1.134)
2nd Decile	6.781	11.338	6.492	8.773	−0.289	(−0.308)
3rd Decile	9.08	13.138	8.576	12.897	−0.504	(−0.388)
4th Decile	6.035	9.721	10.971	16.049	4.936***	(3.865)
5th Decile	7.114	10.719	6.885	8.956	−0.229	(−0.248)
6th Decile	7.11	9.967	8.832	12.894	1.722	(1.483)
7th Decile	7.339	11.208	12.959	15.662	5.620***	(4.523)
8th Decile	10.974	15.251	9.421	13.434	−1.552	(−1.04)

(Continues)

TABLE 3 (Continued)

CO2 emissions deciles	Pre-Paris Mean	Pre-Paris SD	Post-Paris Mean	Post-Paris SD	t-test Difference	t-test S.E.
9th Decile	5.241	8.256	2.703	3.565	−2.538***	(−4.523)
10th Decile	11.012	14.387	7.383	10.321	−3.629**	(−3.082)

Note: The table shows the results of the t-test for differences in means of loan pricing (loan margin in bps) and credit supply measures (loan amount in thousand USD, bank's loan share). The test considers the difference in the mean of each loan-level variable, considered before and after the Paris Agreement. The Pre-Paris period includes the years 2011-2015, while the Post-Paris one considers 2016, 2017, 2018. The t-test is performed for each decile of the distribution of CO2 emissions (in th tonnes). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

$$CL_{t,l,i,f,c} = \beta_0 + \beta_1 CO2_{t,j} + \beta_2 CO2Emissions_{t,f} {}^* CCPI_{t,c} + \beta_3 CO2Emissions_{t,f} {}^* CCPI_{t,c} {}^* Post_t + \beta_4 L_{t,l} + \beta_5 F_{t-1,f} + \beta_6 B_{t,i} + \beta_7 C_{t,c} + \epsilon_{t,l,i,f,c} \quad (1)$$

where the dependent variable *CL* is the cost (in basis points) at time t of the loan l granted by bank i to the borrower f located in country c. *CO2Emissions* quantifies the total carbon emissions in thousands of tonnes for borrowing firm f in year t, while *CCPI* is the Germanwatch's Climate Change Performance Index of the borrower's home country c in year t. The interaction *CO2Emissions**CCPI* captures the annual exposure of a firm to climate change transition due to both its own environmental performance and the engagement towards climate change issues at the country level. The intuition is that for each level of pollution, firms located in countries that are more environmentally conscious are more likely to incur in measures (e.g., sanctions and limitations on certain activities) designed to mitigate their carbon impact. This could affect firms financially and require expensive investments to adjust practices and business models. Consequently, lenders should charge higher interest rates to more exposed firms.[11] The variable *Post* is binary, taking the value 1 after the signing of the Paris Agreement (years 2016 to 2018) and zero otherwise. The coefficient of interest for the triple interaction is β_3, which identifies a firm's overall exposure to climate change risk in the aftermath of Paris Agreement,ì when transition risk is assumed to be higher.

L, F, B, C are vectors of, respectively, loan-year, firm-year, bank-year, and country-year characteristics that according to previous studies can influence loan pricing. In particular, loan-level controls include the loan amount (in logarithms) and maturity (in months), the number of lead arrangers participating in the syndicate, as well as dummies for loan purpose and type, and the presence of covenants, performance pricing grid and collateralization. Time-varying firm characteristics refer to borrowers' size, leverage and profitability, all lagged by 1 year. Bank-level variables control for size, capitalization and profitability of individual banks (the lead arrangers). We incorporate firm-specific and lender-specific time-varying controls to mitigate concerns that our results might be influenced by changes in borrowers' characteristics, which affect their demand, or by fluctuations in banks' credit supply policies. Additionally, time-varying macroeconomic factors, such as shifts in aggregate credit demand and economic growth, that are correlated with changes in both borrowers' vulnerability to CTR and loan metrics, could introduce omitted variable bias. We, therefore, control for GDP per capita and GDP growth in the borrowers' country. We also consider different interest rate environments by controlling for variations in the monetary policy rate.

To better account for specific characteristics on the demand side, we employ fixed effects for borrower industry. We also include bank fixed effects to account for time-invariant characteristics that affect spreads and lending choices. Moreover, in some specifications, we include year fixed effects to capture year-specific

[11]The main empirical challenge of identifying carbon transition risk drivers is that proxies for CTR are available at the country level only (Bolton and Kacperczyk 2023). Adding firm-level variation in carbon emissions, then, allows to mitigate bias concerns which may be related to potentially omitted country-level variables.

movements that may influence the corporate loan market and are common to all banks in the sample. In accordance with the literature, we cluster standard errors at the lender level.

To explore nonlinear relations between our dependent variables and the level of CTR exposure, we replace the continuous measures of CO2 emissions and CCPI score used in Equation (1) with the dummy variables Vulnerable and HighCCPI. The Equation becomes:

$$\begin{aligned} CL_{t,l,i,f,c} = {} & \beta_0 + \beta_1 Vulnerable_{t,f} + \beta_2 Vulnerable_{t,f} * High\ CCPI_{t,c} + \beta_3 Vulnerable_{t,f} * High\ CCPI_{t,c} * Post_t \\ & + \beta_4 L_{t,l} + \beta_5 F_{t-1,f} + \beta_6 B_{t,i} + \beta_7 C_{t,c} + \epsilon_{t,l,i,f,c} \end{aligned} \tag{2}$$

where, we define as vulnerable to transition risks all the firms whose CO2 emissions are above a given percentile in a specific year. Likewise, we include in the High CCPI group all the borrowers located in countries with a CCPI score above a given percentile in the CCPI distribution in a given year. In both cases, the relevant thresholds considered are the 50th and the 75th percentiles.[12]

To investigate whether CTR affects credit allocation policies (**RQ2**), we follow a two-pronged approach. First, we use the Facility-Lead Arranger data set and estimate the above specifications employing the LoanAmount as dependent variable.[13] This is the logarithm of total syndicated loan amount granted to a given borrower in a given fiscal year. Second, to examine whether and how banks modify their loan portfolio mix after the Paris Agreement (i.e., in the post-Paris Agreement), we exploit the Lender-Borrower data set and employ *LoanShare* as dependent variable.[14]

Finally, due to the nature of the data and the characteristics of the syndicated loan market, a certain data asymmetry is expected. For example, in line with Delis et al. (2017), the composition of our sample shown in Table A1 reflects the fact that syndicated loans are particularly developed among US companies. To allow for this feature of the loan syndication market, depending on the specification, standard errors are clustered at the bank and country level.[15]

4 | RESULTS

4.1 | Main results

We first investigate whether the cost of syndicated loans is affected by exposure to CTR, particularly so during periods in which climate transition risk is increasing, as after the signing of the Paris Agreement on December 15th 2015.

Table 4 reports the results of the analysis on loan margin as dependent variable by using the Facility-Lead Arranger data set. In Columns (1) to (3), we progressively add to the specification the different components of our CTR proxy: CO2 Emissions, the post-COP21 dummy, and CCPI.[16] Findings in Column (1) show that higher CO2 emissions are strongly positively associated with the cost of loans (the estimated coefficient for CO2 is

[12]From the definitions of the Vulnerable and High CCPI dummies, it follows that they are both time-varying, since the threshold is computed over the sample for each year.

[13]When the dependent variable is LoanAmount, we employ loan margin as a control variable. In unreported results, we find baseline findings for loan amount to be robust to the inclusion/exclusion of loan margin among the control variables.

[14]We employ the same specifications described for the estimation of Equation (1) and Equation (2). We control for the average maturity and the average loan margin of syndicated transactions in which each lender participates in a given year. In unreported results, we find baseline findings to be robust to the inclusion/exclusion of average loan margin among the control variables.

[15]Following Delis et al. (2021), since the treatment variable of interest will be observed at national level, clustering at country level is preferable when (country-specific) CCPI is considered.

[16]We do not report the results of the specification featuring the CO2 emissions * CCPI interaction, as we do not detect statistically significant effects for any of the dependent variables considered.

TABLE 4 Loan pricing, carbon emissions, country-level engagement towards climate change, and the Paris Agreement.

Loan margin (bps)	CO2 Emissions (1)	CO2 Emissions * Post (2)	CO2 Emissions * CCPI * Post (3)
CO2	0.000286***	0.000430***	0.00191*
	(7.71e-05)	(8.40e-05)	(0.00107)
CCPI			0.339
			(0.298)
CO2 * CCPI			−2.55e-05
			(1.81e-05)
Post		1.828	18.40
		(3.276)	(16.02)
CO2 * Post		−0.000500***	−0.00447*
		(0.000149)	(0.00231)
CCPI * Post			−0.257
			(0.264)
CO2 * CCPI * Post			6.77e-05*
			(3.86e-05)
Observations	3,085	3,085	3,024
R-squared	0.589	0.577	0.581
Adjusted R-Squared	0.492	0.541	0.554
Loan Purpose FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Firm's industry FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time FE	Yes	No	No
Firm's country FE	No	No	No
Firm's country GDP controls	Yes	Yes	Yes
Clustered SE	Bank	Bank	Bank

Note: The table presents OLS estimation results. The dependent variable is Loan Margin (in bps). The main regressor is CO2, which refers to total carbon emissions of firm i in year t, measured in thousands of tonnes; it is interacted with the firm's country CCPI. The dummy variable Post takes value 1 for the years 2016, 2017, 2018, and zero otherwise. All specifications include loan, bank, firm and firm's country time-varying controls, along with loan purpose and loan type fixed effects, firms' industry fixed effects, and bank fixed effects. Column (1) also includes year fixed effects. The data set of reference is the Facility-Lead Arranger configuration.

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

positive and statistically significant at 1% level). The economic significance of the effect, however, is small: a one-standard deviation change in borrower's CO2 emissions is associated with an increase in loan margin of 8 basis points. Furthermore, a min-max change in CO2 emissions (which amounts to a 232 million tonne-variation in carbon emissions) is associated with a 66 basis points higher loan margin. Table 4, Columns (2) and (3), shows whether any change in loan prices can be detected after the signing of the Paris Agreement in December 2015. We find positive estimated coefficients for CO2 emissions that turn negative for the CO2*Post interaction, suggesting that more polluting firms were charged relatively lower loan prices from 2016 onwards. Column (3) also shows the results of the estimation of Equation (1). When the stringency of climate policy (CCPI) is taken into account, this result is only marginally attenuated, as the coefficient of the triple interaction CO2*CCPI*Post is positive and statistically significant at the 10% level. The sum of the relevant marginal effects does not yield statistically significant results.[17]

Table 5 shows the results of our analysis on CTR and credit supply. We find a positive relation between loan amount and borrowers' carbon emissions (Column (1)), although the estimated coefficient is small: a one-standard deviation (min-max) change in borrower's CO2 emissions is associated with a loan amount higher by 0.12 (1.74) percent. When we consider COP21, we find the estimated coefficient for the Post-Paris Agreement dummy to be positive and statistically significant at the 1% level in both Columns (2) and (3). In Column (2), while coefficient estimates for CO2 Emissions and Post are positive and statistically significant, that for the interaction term is negative and statistically significant. Column (3) shows that, when COP21 and CCPI enter the picture, the estimated coefficient for the triple interaction is positive, although statistically insignificant.

In Columns (4) – (6) of Table 5 we investigate how banks adjust their portfolio mix to higher CTR by using the Lender-Borrower level data set and employing *LoanShare* as dependent variable.[18] We find the coefficient of CO2 emissions to be positive and statistically significant, although rather small (Column (4)). This implies that a one-standard deviation (min-max) change in borrower's CO2 emissions is associated with a loan share higher by 0.85 (8.8) percent. We then focus on the analysis employing the post-COP21 dummy. Evidence from Ivanov et al. (2023) and Reghezza et al. (2021) points in the direction of a credit reallocation away from more polluting borrowers as concerns over CTR increase. We indeed find a negative and statistically significant coefficient for the CO2 Emissions*Post interaction (Column (5)). However, when we estimate Equation (1), we find no evidence of any such effect (the estimated coefficient for the triple interaction of interest in Column (6) is negative, although not statistically significant).

To summarize, our main findings on loan pricing, amount, and portfolio composition point to the following considerations. First, results vary depending on whether or not we account for the Paris Agreement and country climate policy stringency. Second, when considering all dimensions of CTR (firm-level pollution, the signining of the Paris Agreement, and the efforts to combat climate change in countries where polluters are located), we find only limited evidence of banks charging polluting firms higher interest rates, with no effects on credit supply.

4.2 | Investigating nonlinear relations between bank behaviour and climate change risk

In this section, we exploit the heterogeneity in our data set by looking at lending practices in banks exposed to vulnerable borrowers (Table 6 and Table 7). To this end, we focus on the right-most part of both the carbon emissions and CCPI distributions and estimate Equation (2).

[17]Following Brambor et al. (2006), we graphically examine the marginal effect of CO2 Emissions on the cost of loan over different values of the interacted variable CCPI. The analysis, which is available upon request, shows that, in the Post-Paris period, the impact of CO2 emissions on loan pricing increases as climate policy in the borrower's country becomes more stringent. However, this effect is not statistically significant.

[18]Since the variable *LoanShare* is constructed on the basis of each lender's share in the loan granted by the syndicate, the number of loans considered in the Lender-Borrower data set is lower compared to the other two data sets. This is expected, as DealScan does not provide information on lender share for all its entries.

TABLE 5 Credit supply: carbon emissions, country-level engagement towards climate change, and the Paris Agreement.

	Dep. Var. Loan Amoun (log)			Dep. Var. Loan Share (%)		
	CO2 Emissions	CO2 Emissions * Post	CO2 Emissions * CCPI * Post	CO2 Emissions	CO2 Emissions * Post	CO2 Emissions * CCPI * Post
	(1)	(2)	(3)	(4)	(5)	(6)
CO2	4.35e-06***	4.69e-06***	−7.60e-06	3.79e-05***	5.36e-05***	−1.53e-05
	(1.49e-06)	(1.56e-06)	(1.31e-05)	(1.13e-05)	(1.17e-05)	(0.000135)
CCPI			0.0215***			0.0232
			(0.00353)			(0.0406)
CO2 * CPPI			2.06e-07			1.29e-06
			(2.19e-07)			(2.38e-06)
Post		0.154***	1.219***		1.669***	−0.126
		(0.0303)	(0.201)		(0.365)	(2.477)
CO2 * Post		−2.94e-06**	−1.57E-05		−4.53e-05***	0.000111
		(1.41e-06)	(2.58e-05)		(1.11e-05)	(0.000174)
CCPI * Post			−0.0180***			0.0393
			(0.00324)			(0.0466)
CO2 * CCPI * Post			2.15E-07			−2.93e-06
			(4.28e-07)			(3.26e-06)
Observations	3,024	3,085	3,024	4,436	4,436	4,436
R-squared	0.679	0.673	0.683	0.526	0.523	0.524
Adjusted R-Squared	0.651	0.645	0.655	0.496	0.493	0.494
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm's industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes	No	No
Firm's country FE	No	No	No	No	No	No
Firm's country GDP controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Bank	Bank	Bank	Bank	Bank	Bank

Note: The table presents OLS estimation results. In columns (1)-(3), the dependent variable is the logarithm of loan amount (converted in thousands USD). The data set of reference is the Facility-Lead Arranger one. In columns (4)-(6), the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year, in percentage points). The data set of reference is the Lender-Borrower configuration. The main regressor is CO2, which refers to total carbon emissions of firm i in year t, measured in thousands of tonnes; it is interacted with firm's country CCPI and a time indicator for the Post-COP21 period. The dummy variable Post takes value 1 for the years 2016, 2017, 2018, and zero otherwise. All specifications include loan, bank, firm and firm's country time-varying controls, along with loan purpose and loan type fixed effects, firms' industry fixed effects, and bank fixed effects. Columns (1) and (4) also include year fixed effects.

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

TABLE 6 Loan pricing. Vulnerable borrowers, High CCPI, and the Paris Agreement.

	Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Loan margin (bps)	**(1)**	**(2)**	**(3)**	**(4)**
Vulnerable	−20.42**	−7.815	−14.76	−15.99**
	(8.007)	(7.213)	(10.10)	(8.087)
High CCPI	−11.98*	8.163	10.41**	27.90***
	(6.192)	(7.365)	(5.095)	(9.087)
Vulnerable * High CCPI	23.67*	1.310	−23.78*	−46.08***
	(13.47)	(11.90)	(14.30)	(16.73)
Post Paris	−0.368	4.478	4.757	1.802
	(5.497)	(5.877)	(5.012)	(4.952)
Vulnerable * Post Paris	−5.408	−19.14**	−28.00***	−25.92***
	(8.394)	(8.116)	(10.67)	(9.509)
High CCPI * Post Paris	4.699	−4.844	−10.62	−4.667
	(8.436)	(9.641)	(8.249)	(8.804)
Vulnerable * High CCPI * Post Paris	−6.727	38.96***	23.99	45.40
	(14.07)	(14.61)	(25.11)	(28.95)
Observations	3,024	3,024	3,024	3,024
R-squared	0.577	0.579	0.584	0.588
Adjusted R-Squared	0.563	0.566	0.573	0.577
Loan Purpose FE	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Firm's industry FE	Yes	Yes	Yes	Yes
Firm's country GDP controls	Yes	Yes	Yes	Yes
Firm's Country FE	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: The table presents OLS estimation results of Equation (2). The dependent variable is loan margin (in basis points). Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. Similarly, borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). The dummy variable Post takes value 1 for the years 2016, 2017, 2018, and zero otherwise. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country. Furthermore, all specifications include bank fixed effects. The data set of reference is the Facility-Lead Arranger configuration.

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

TABLE 7 Credit supply. Vulnerable borrowers, high country engagement towards climate change, and the Paris Agreement.

	Dep. Var.: Loan Amount (log)				Dep. Var.: Loan Share (%)			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerable	0.301***	0.241***	0.0243	−0.0224	1.704***	1.788***	2.418***	2.539***
	(0.0804)	(0.0762)	(0.0866)	(0.0628)	(0.551)	(0.564)	(0.477)	(0.481)
High CCPI	0.894***	0.705***	0.671***	0.415***	0.509	0.993	0.244	1.066
	(0.106)	(0.106)	(0.0969)	(0.0908)	(1.100)	(1.112)	(0.842)	(0.766)
Vulnerable * High CCPI	−0.550***	−0.490***	−0.170	0.0456	2.647***	6.867***	7.207***	19.80***
	(0.165)	(0.115)	(0.138)	(0.129)	(0.987)	(1.705)	(1.308)	(3.248)
Post Paris	0.666***	0.480***	0.432***	0.306***	1.214***	1.189***	0.437	0.785*
	(0.0991)	(0.0759)	(0.0923)	(0.0666)	(0.415)	(0.388)	(0.477)	(0.449)
Vulnerable * Post Paris	−0.648***	−0.467***	−0.377**	−0.339*	−0.361	0.254	1.269**	1.328**
	(0.119)	(0.106)	(0.174)	(0.178)	(0.565)	(0.577)	(0.641)	(0.663)
High CCPI * Post Paris	−0.758***	−0.543***	−0.471***	−0.383***	5.039***	4.465***	5.699***	2.156*
	(0.114)	(0.110)	(0.1000)	(0.0913)	(1.725)	(1.631)	(1.245)	(1.304)
Vulnerable * High CCPI * Post Paris	0.885***	0.385***	0.745***	0.663*	−2.310	−12.56***	−8.830***	−24.26***
	(0.161)	(0.138)	(0.248)	(0.374)	(2.072)	(2.127)	(2.361)	(3.420)
Observations	3,024	3,024	3,024	3,024	4,378	4,378	4,378	4,378
R-squared	0.691	0.684	0.688	0.682	0.529	0.530	0.538	0.545
Adjusted R-Squared	0.601	0.589	0.597	0.586	0.513	0.521	0.524	0.530
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 7 (Continued)

	Dep. Var.: Loan Amount (log)				Dep. Var.: Loan Share (%)			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm's industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm's country GDP controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm's Country FE	No	Yes	No	No	No	No	No	No
Bank FE	Yes	YES	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Note: The table presents OLS estimation results of Equation (2). In columns (1)-(4), the dependent variable is the logarithm of loan amount (converted in thousands USD). The Facility-Lead Arranger configuration is the reference data set. In columns (5)-(8), the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year, in percentage points). The Lender-Borrower configuration is the reference data set. Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. Similarly, borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). The dummy variable Post takes value 1 for the years 2016, 2017, 2018, and zero otherwise. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country. Furthermore, all specifications include bank fixed effects.

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

The results of the OLS estimation on loan margin in Table 6 show that, before 2016, vulnerable firms operating in low-CCPI countries borrowed in the syndicated loans market at prices that were on average lower than for non-vulnerable borrowers located in the same group of countries. This is true independently of the vulnerability threshold employed, as the estimated coefficients for the dummy Vulnerable show. Estimates for the triple interaction term are consistently positive across all specifications and highly significant in countries with a CCPI index in the top 25 percent of the distribution. Hence, in the post-Paris years, vulnerable borrowers were charged, on average, higher loan prices in countries with particularly strict climate policies compared to countries with a more lenient approach. Specifically, considering Column (2) which yields a 1%-statistically significant estimated coefficient for the triple interaction, it appears that, from 2016 onwards, vulnerable borrowers in top-25 CCPI countries were charged, on average, 44 basis points more[19] than equally vulnerable borrowers located in bottom 75-CCPI countries. Moreover, in the post-COP21 period, in top25-CCPI countries, vulnerable borrowers paid prices 13 basis points higher,[20] on average, than those applied to non-vulnerable borrowers.

Table 7 reports the results for the credit supply analysis. As far as loan amount is concerned (Columns (1) – (4)), we find that the estimated coefficient for Vulnerable is statistically significant (and positive) only in the first two columns while the coefficient on HighCCPI is consistently positive and statistically significant. The negative coefficient for CO2 Emission*HighCCPI suggests that, in the pre-COP21 period, vulnerable borrowers located in countries particularly engaged in combating climate change were on average granted lower loan amounts compared to either non-vulnerable borrowers in high-CCPI countries or to vulnerable borrowers in low-CCPI countries. The estimation of the triple interaction yields positive and statistically significant values across different thresholds of firm vulnerability and country-level engagement in contrasting climate change. If, consistent with the loan pricing case, we consider the specification in Column (2), we find that from 2016 onwards, being vulnerable is associated with 6% higher loan amounts in high-CCPI countries compared to the average amount granted to vulnerable borrowers in low-CCPI countries. However, the volume of new loans granted to vulnerable borrowers was, on average, 33% lower for vulnerable borrowers compared to non-vulnerable ones in high CCPI countries after the Paris Agreement. If we consider the more extreme polluters, (i.e., the specifications in Column (3) and (4)), this latter effect is reversed, with vulnerable borrowers being associated with 22%-34% higher loan amounts.

When examining the relationship between CTR and Loan Share, (Columns (5)-(8)), we find that the amount of syndicated loans issued to vulnerable borrowers located in low-CCPI countries before 2016, on average, tends to represent a larger share of banks' annual gross loan compared to loans issued to non-vulnerable borrowers in similar countries, all else being equal.

Remarkably, the estimated coefficients for the triple interaction are negative across all specifications and statistically significant in all cases but one. The climate policy stringency of the borrower's country plays a role in that the magnitude of the triple interaction coefficients is higher when the top25 definition for High CCPI is considered – independently of the definition of borrower's vulnerability. Specifically, when considering Column (2), which shows a statistically significant 1% estimated coefficient for the triple interaction, it appears that, in the post-COP21 period, in high-CCPI countries, vulnerable borrowers accounted for a share of newly-issued syndicated lending to gross loans lower by 3.65 percentage points,[21] on average, compared to non-vulnerable borrowers operating in the same group of countries.

Holding vulnerability fixed and considering the period from 2016 onwards, the magnitude of the effect is smaller: vulnerable borrowers located in countries particularly sensitive to climate issues accounted, on average,

[19] The result is obtained by combining the estimated coefficients reported in Column (2) as follows: (−7.815 + 8.163 + 1.31 + 4.478-19.14-4.844 + 38.96)-(−7,815 + 4.478-19.14) = 43.59.

[20] The result is obtained by combining the estimated coefficients reported in Column (2) as follows: (−7.815 + 8.163 + 1.31 + 4.478-19.14-4.844 + 38.96)-(8.163 + 4.478-4.84) = 13.32.

[21] The result is obtained by combining the estimated coefficients reported in Column (2) as follows: (1.788 + 0.993 + 6.867 + 1.189 + 0.254 + 4.465-12.56)-(0.993 + 1.189 + 4.465) = −3.65.

for a syndicated to total lending share lower by 0.24 percent compared to equally vulnerable borrowers located in low-CCPI countries.[22]

Overall, this analysis documents that banks have originated larger amounts of loans at higher costs to vulnerable borrowers located in climate resilient countries in the post-Paris Agreement period. At the same time, however, the results show that credit reallocation has occurred, at the expense of highly polluting borrowers, since the Paris Agreement.

4.3 | Extensions and robustness checks

This section serves a twofold purpose. First, it goes deeper into the investigation of potential additional drivers of CTR. Second, it provides checks ensuring the robustness of the baseline results.

4.3.1 | Further potential CTR risk drivers

Industry-level vulnerability

In our main specification, we identify firms as particularly vulnerable to CTR by comparing their CO2 emissions in a year to the carbon emissions reported by all the other firms in the sample for the same year. Hence, our vulnerability measure does not consider industry-level peculiarities. On the other hand, it singles out firms whose carbon emissions are indeed substantial. However, an intuitive, alternative approximation for borrowers' vulnerability to CTR is precisely the industry in which firms operate: when facing increasing transition risks, lenders might reduce their exposure to industries that are deemed to be more likely to be affected by climate change mitigation regulation. Moreover, it is possible that, as Ehlers et al. (2022) document, mitigation policies, to achieve substantial reductions more quickly, are mainly targeted at particularly carbon-intensive industries and sectors.

We thus analyse banks' behaviour towards highly polluting industries. We resort to the classification of high-carbon industry sectors suggested by Ehlers et al. (2022) and include a dummy variable that groups borrowers operating in industries related to oil, coal, gas, utilities, materials and transport. In unreported results, we perform the estimation by progressively adding the 2-digit SIC industries relative to each of the carbon-intensive activites listed above, and find consistent results for narrower and broader definitions of vulnerability of the industry.

Table 8 shows the results. In contrast with the baseline findings, the analysis on loan margin (Columns (1) and (2)) highlights that, in low-CCPI countries before 2016, borrowers operating in highly-polluting industries receive, on average, higher loan prices compared to borrowers in other industries. Nevertheless, as in Table 6, the coefficients of the triple interaction are positive and statistically significant. This result indicates that, in the post-Paris Agreement years, borrowers operating in high-carbon intensive industries were charged on average higher loan prices in countries with particularly strict climate policies compared to borrowers in other industries in countries with a more lenient approach. In particular, if we consider the 75th percentile of CCPI as threshold (Column (2)) as in the previous paragraph, estimation results show that, from 2016 onwards, vulnerable borrowers in top-25 CCPI countries were charged on average 56 basis points more than equally vulnerable borrowers located in bottom 75-CCPI countries. Moreover, in the post-COP21 period, in top25-CCPI countries, vulnerable borrowers paid prices 131 basis points higher, on average, than those applied to non-vulnerable borrowers.

As for loan amounts (Columns (3) and (4)), the results do not significantly differ in either magnitude or statistical significance from those in Table 7. Therefore, it is not just firm-level carbon emission performance that is associated with banks' incorporation of CTR, as suggested by the previous analyses. This investigation underscores that lenders attribute relatively higher premia and loan amounts to the most polluting industries.

[22]The result is obtained by combining the estimated coefficients reported in Column (2) as follows: (1.788 + 0.993 + 6.867 + 1.189 + 0.254 + 4.465-12.56)-(1.788 + 1.189 + 0.254) = −0.24.

TABLE 8 Loan margin and credit supply. Industry-based vulnerability.

	Dep. Var.: Loan Margin (bps)		Dep. Var.: Loan amount (log)		Dep. Var.: Loan Share (%)	
	High CCPI top50	High CCPI top25	High CCPI top50	High CCPI top25	High CCPI top50	High CCPI top25
	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerable Industry	74.06**	98.92***	−0.241	−0.230	−23.80***	−25.65***
	(33.98)	(35.24)	(0.396)	(0.411)	(4.043)	(4.145)
High CCPI	−8.143	6.602	0.654***	0.567***	2.263*	5.881***
	(7.025)	(10.56)	(0.0961)	(0.0843)	(1.266)	(1.366)
Vulnerable Industry * High CCPI	15.32	8.015	−0.126	−0.310***	−0.802	−3.748**
	(9.583)	(13.08)	(0.136)	(0.102)	(1.373)	(1.758)
Post	2.371	−0.610	0.403***	0.305***	1.422***	1.660***
	(3.790)	(3.559)	(0.0618)	(0.0501)	(0.481)	(0.422)
Vulnerable Industry * Post	−23.69**	−20.43**	−0.282**	−0.271**	−1.173**	−0.816*
	(9.617)	(8.403)	(0.118)	(0.133)	(0.522)	(0.470)
High CCPI * Post	−16.71**	−3.725	−0.572***	−0.499***	1.482	−4.422***
	(8.045)	(8.785)	(0.0818)	(0.0711)	(1.454)	(1.544)
Vulnerable Industry * High CCPI * Post	61.92***	44.88**	0.759***	0.605***	6.115***	7.093***
	(16.08)	(18.87)	(0.178)	(0.194)	(1.933)	(2.189)
Observations	3,024	3,024	3,024	3,024	4,378	4,378
R-squared	0.582	0.579	0.688	0.681	0.527	0.524
Adj. R-Squared	0.546	0.542	0.661	0.654	0.497	0.494
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm's Sectors FE	No	No	No	No	No	No
GDP controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower's country FE	No	No	No	No	No	No
Clustered SE	Bank	Bank	Bank	Bank	Bank	Bank

Note: The table presents OLS estimation results. In columns (1)-(2), the dependent variable is loan margin (in basis points); in columns (3)-(4), the dependent variable is the logarithm of loan amount; in columns (5)-(6), the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year, in percentage points). The reference data set is Facility-Lead Arranger for columns (1)-(4) and Lender-Borrower for columns (5)-(6). We follow Ehelers et al., 2021 for the definition of carbon-intensive industries: the dummy variable Vulnerable Industry includes SIC-subindustries corresponding to the following sectors: Oil, Coal, Gas, Utilities, Materials, and Transport. Borrowers' countries are classified into high-climate sensitive countries and low-climate sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided).

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The estimation using Loan Share contrasts results in Table 7 on several aspects: for low-CCPI countries, operating in a highly-polluting industry is associated with a lower loan share, especially in the post-COP21 period. Additionally, the coefficients for the triple interaction are positive and statistically significant. Hence, in the post-COP21 period, syndicated loans are issued to carbon-intensive industries at higher prices and in larger amounts compared to less polluting industries; they also account for a larger share of banks' gross loans, all else being equal. Nevertheless, in the post-COP21 period, loans to vulnerable borrowers from high-CCPI countries accounted for a share of newly-issued syndicated lending to gross loans that was 23 percentage points lower,[23] on average, compared to loans to non-vulnerable borrowers operating in the same group of countries. This effect confirms the findings of the previous section and emphasizes the importance of properly measuring bank exposure by considering not only polluting borrowers but also at polluting industries.

In an additional test, we employ an alternative proxy for CTR vulnerabilty of borrowers. We construct a dummy that takes value 1 if the carbon emissions of the borrowing firm exceed either the 50th or the 75th percentile of the distribution of carbon emissions in a 2-digit subindustry and country. Hence, we have a measure of vulnerability that accounts for both industry-specific and borrower-specific characteristics. Unlike our main vulnerability dummy (which relates each firm to the whole sample, serving as an "absolute measure" of vulnerability), this measure allows us to identify vulnerable borrowers in relative terms by comparing each firms to its peers in the industry and the country in which it operates. Results, available upon request, are consistent with our main analysis.

Geographic patterns

With the aim of delving further into possible drivers of CTR, we examine whether banks adapt their behavior according to either the location of borrowing firms or to their own location, focusing in particular on the comparison between Europe and the United States.

Since the Paris Agreement, European countries, and the EU in particular, have adopted ambitious legislation across multiple policy areas to implement its international commitments on climate change (e.g. the setting of binding emission targets for key sectors of the economy to substantially reduce greenhouse gas emissions, the launch of the European Green Deal in December 2019 and the entry into force of the Taxonomy Regulation in July 2020). Besides the latest development, in Europe, climate policy gained a prominent position in the political agenda even before the climate summit in Kyoto in December 1997, spurred by the annexion to the EU of countries with high environmental standards (Austria, Finland and Sweden) in 1995. The first structured policy program targeting environmental issues (the European Climate Change Program) dates back to 1998 and was followed by the Climate Change and Energy Package in 2007 and by the European Green Deal in 2019 (Selin and VanDeveer 2015; European Climate Policy Hub).[24] As a result, EU environmental standards are among the highest in the world (Cifuentes-Faura 2022). By contrast, in the last years of our sample period, the US experienced the withdrawal from the Paris Agreement, announced by President Trump in June 2017 and formally enacted in November 2017. More recently, a growing number of US states have passed laws to restrict the use of ESG factors in making investment and business decisions. According to Donefer (2023), proponents of these laws claim ESG threatens investment returns and uses economic power to implement business standards beyond those required by law.

Building on this, in Table 9 we split the sample according to whether borrowing firms are located in Europe (including the UK) or in the US. We check whether and how banks' pricing and lending choices relate to CTR differently in the two subsamples in the pre-post Paris Agreement period. The specification features the time-varying dummy variables for borrowers' firm-level vulnerability, while we do not include any measure of country engagement in climate action so as to avoid multicollinearity issues. We do find consistent and significant discrepancies in the estimated coefficients between the two subsamples only as far as loan pricing is concerned. Although the coefficients for the triple interaction shows opposite sign in Columns (1) and (2), the analysis of the relevant marginal effects is consistent across the two specifications. It points to lower loan rates for vulnerable borrowers in the post-COP21 period, ceteris paribus, with the difference with

[23]The result is obtained by combining the estimated coefficients reported in Column (2) as follows: (−25.65 + 5.881-3.748 + 1.660-0.816-4.422 + 7.093)-(5.881 + 1.66-4.422) = −23.121.

[24]A detailed timetable of EU climate policy can be found at http://climatepolicyinfohub.eu/european-climate-policy-history-and-state-play.

TABLE 9 Loan pricing and credit supply. CTR and borrower location.

	Dep. Var.: Loan Margin (bps))			
	European Firms		US Firms	
	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25
Panel A	**(1)**	**(2)**	**(3)**	**(4)**
Vulnerable	−23.01**	−66.65***	−14.13	5.302
	(10.93)	(9.882)	(8.625)	(6.747)
Post Paris	−12.36*	−7.066	−15.01**	−11.85*
	(6.378)	(5.257)	(7.132)	(6.109)
Vulnerable * Post Paris	9.943	−22.36**	9.571	1.457
	(9.145)	(10.79)	(7.955)	(7.396)
Observations	1,604	1,604	628	628
R-squared	0.746	0.767	0.764	0.763
Adjusted R-Squared	0.718	0.742	0.719	0.717

	Dep. Var.: Loan Amount (log)				Dep. Var.: Loan Share (%)			
	European firms		US firms		European firms		US firms	
	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Vulnerable	−0.201*	−0.0452	0.502***	0.201*	5.910***	2.049**	−0.0108	2.314***
	(0.102)	(0.0856)	(0.154)	(0.101)	(1.198)	(0.945)	(0.454)	(0.623)
Post Paris	0.0433	−0.0245	0.379***	0.281***	4.725***	3.581***	0.799	0.243
	(0.0613)	(0.0526)	(0.0831)	(0.101)	(1.020)	(0.616)	(0.548)	(0.562)
Vulnerable * Post Paris	−0.265**	−0.220*	−0.536**	−0.548***	−1.554	−0.742	−0.988	−0.450
	(0.111)	(0.119)	(0.229)	(0.134)	(1.120)	(1.698)	(0.649)	(0.553)

TABLE 9 (Continued)

	Dep. Var.: Loan Amount (log)				Dep. Var.: Loan Share (%)			
	European firms		US firms		European firms		US firms	
	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25	Vulnerable: top50	Vulnerable: top25
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	1,604	1,604	628	628	637	637	2,839	2,839
R-squared	0.807	0.804	0.497	0.494	0.801	0.792	0.551	0.554
Adjusted R-Squared	0.787	0.784	0.402	0.399	0.757	0.747	0.523	0.526

Note: The table presents OLS estimation results. In Panel A, the dependent variable is loan margin (in basis points). As for Panel B, in columns (1)-(4), the dependent variable is the logarithm of loan amount (converted in thousands USD) and Facility-Lead Arranger is the reference data set. In columns (5)-(8), the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year), and Lender-Borrower is the relevant data set. Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. We split the sample according to whether the borrowing firm is located in a European country (including the UK) or in the United States. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country.

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

respect to non-vulnerable borrowers ranging between 13 and 89 basis points, depending on the vulnerability threshold employed. Moreover, for European vulnerable borrowers, it appears that loan rates have experienced a decline after the Paris Agreement, ranging between 2 and 29 basis points. On the other hand, the US borrowing firms subsample does not yield statistically significant coefficients.

Additionally, in Tables 10 and 11 we employ the models with binary explanatory variables for borrower's vulnerability and climate-related efforts of the borrower's country, and look for differential behavioral patterns of

TABLE 10 Loan pricing. CTR and bank location.

	European Banks				US Banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
Loan amount (log)	CCPI: top50 (1)	CCPI: top25 (2)	CCPI: top50 (3)	CCPI: top25 (4)	CCPI: top50 (5)	CCPI: top25 (6)	CCPI: top50 (7)	CCPI: top25 (8)
Vulnerable	−46.58***	−4.966	−69.73***	−37.31***	−9.993	−5.052	5.310	0.949
	(14.87)	(12.83)	(13.55)	(10.37)	(8.271)	(6.656)	(5.152)	(6.487)
High CCPI	−26.82*	12.18	−10.69	29.97***	13.07	−5.063	27.11	−8.266
	(15.80)	(10.70)	(8.891)	(10.67)	(19.85)	(11.40)	(21.92)	(12.16)
Vulnerable * High CCPI	58.52***	24.13*	35.51***	−15.51	31.96*	11.55	−2.630	23.94
	(20.31)	(14.22)	(13.05)	(17.14)	(18.04)	(18.23)	(16.25)	(16.25)
Post Paris	−8.090	12.05	−11.85	−5.602	−10.18	−12.07**	−8.114*	−10.54*
	(15.84)	(10.47)	(11.00)	(7.883)	(6.301)	(4.910)	(4.558)	(4.972)
Vulnerable * Post Paris	−0.731	−42.82***	−15.42	−36.23**	8.895	4.906	4.872	4.185
	(18.02)	(15.59)	(17.29)	(15.76)	(10.34)	(9.005)	(5.593)	(2.693)
High CCPI * Post Paris	6.158	−21.03	−1.761	−11.06	12.22	17.21	25.00	44.53**
	(18.10)	(12.59)	(13.40)	(11.66)	(24.01)	(15.57)	(30.23)	(19.06)
Vulnerable * High CCPI * Post Paris	−27.22	36.36**	3.822	37.06	5.641	49.15	−56.32	−22.53
	(21.39)	(17.70)	(25.12)	(31.01)	(20.27)	(36.58)	(54.05)	(45.65)
Observations	1,318	1,318	1,318	1,318	729	729	729	729
R-squared	0.659	0.664	0.670	0.673	0.730	0.730	0.729	0.725
Adjusted R-Squared	0.636	0.641	0.648	0.650	0.697	0.696	0.695	0.691

Note: The table presents OLS estimation results. The dependent variable is loan margin (in basis points). Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. Similarly, borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). We split the sample according to whether the lender is a bank located within the European Union (and UK) or in the United States. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country.

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

TABLE 11 Credit supply. CTR and bank location.

	European Banks				US Banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Loan amount (log)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A Dep. Var.: Loan Amount (log)								
Vulnerable	0.468***	0.195	0.184	0.0439	0.284	0.384**	−0.00176	−0.0124
	(0.166)	(0.130)	(0.170)	(0.0951)	(0.184)	(0.128)	(0.0883)	(0.119)
High CCPI	1.135***	0.850***	0.875***	0.625***	0.492**	0.541**	0.557***	0.271
	(0.159)	(0.112)	(0.162)	(0.0875)	(0.166)	(0.193)	(0.0898)	(0.176)
Vulnerable * High CCPI	−0.743***	−0.453***	−0.281	−0.100	0.197	−0.126	0.0756	0.482**
	(0.150)	(0.131)	(0.177)	(0.166)	(0.612)	(0.248)	(0.242)	(0.221)
Post Paris	1.291***	0.551***	0.744***	0.350***	0.528***	0.522***	0.362***	0.300***
	(0.262)	(0.199)	(0.238)	(0.0986)	(0.0923)	(0.0850)	(0.0860)	(0.0648)
Vulnerable * Post Paris	−1.430***	−0.614**	−0.840***	−0.613***	−0.633***	−0.712***	−0.565**	−0.561*
	(0.237)	(0.236)	(0.252)	(0.131)	(0.205)	(0.161)	(0.235)	(0.265)
High CCPI * Post Paris	−1.309***	−0.567***	−0.647***	−0.350***	−0.477	−0.614**	−0.759**	−0.575*
	(0.243)	(0.197)	(0.228)	(0.0965)	(0.283)	(0.266)	(0.285)	(0.295)
Vulnerable * High CCPI * Post Paris	1.756***	0.596**	0.973***	0.705	−0.0217	0.171	1.173**	0.987
	(0.241)	(0.267)	(0.324)	(0.430)	(0.369)	(0.537)	(0.527)	(0.607)
Observations	1,318	1,318	1,318	1,318	729	729	729	729
R-squared	0.789	0.775	0.779	0.775	0.512	0.509	0.513	0.510
Adjusted R-Squared	0.775	0.761	0.765	0.760	0.452	0.449	0.452	0.450
Panel B Dep. Var.: Loan Share (%)								
Vulnerable	0.552	1.126	1.209	2.146*	−0.311	−0.404	1.410	1.363
	(1.115)	(1.228)	(0.996)	(1.107)	(0.750)	(0.780)	(0.931)	(0.884)
High CCPI	0.822	2.835*	0.686	2.798**	6.154*	1.144	3.611*	2.254*
	(1.825)	(1.585)	(1.214)	(1.094)	(3.552)	(1.412)	(1.998)	(1.153)
Vulnerable * High CCPI	2.589	7.659***	6.330**	15.96***	−0.190	8.249	7.873**	20.33***
	(1.817)	(2.780)	(2.571)	(4.501)	(3.888)	(5.565)	(2.991)	(7.359)
Post Paris	1.207	1.306	0.613	1.736**	0.132	−0.0498	−0.891	−0.751
	(0.901)	(0.832)	(0.800)	(0.783)	(0.730)	(0.761)	(0.821)	(0.824)
Vulnerable * Post Paris	−0.317	1.590	0.698	1.429	−1.957	−1.448	0.0940	−0.165
	(1.329)	(1.295)	(0.882)	(1.137)	(1.181)	(1.149)	(1.104)	(1.150)
High CCPI * Post Paris	6.643***	5.148**	6.774***	2.736	−2.974	1.772	5.531	−0.473
	(2.026)	(2.145)	(1.658)	(1.776)	(4.599)	(2.582)	(4.904)	(2.518)

(Continues)

TABLE 11 (Continued)

	European Banks				US Banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Loan amount (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerable * High CCPI * Post Paris	−0.123	−14.56***	−2.236	−25.00***	4.079	−10.73	−18.49***	−23.59**
	(2.833)	(3.294)	(4.132)	(5.252)	(6.467)	(6.597)	(6.362)	(9.554)
Observations	1,190	1,190	1,190	1,190	1,496	1,496	1,496	1,496
R-squared	0.457	0.462	0.464	0.475	0.334	0.332	0.337	0.337
Adjusted R-Squared	0.431	0.437	0.439	0.450	0.311	0.309	0.314	0.314

Note: The table presents OLS estimation results. In Panel A, the dependent variable is the logarithm of loan amount (converted in thousands USD) and Facility-Lead Arranger is the reference data set. In Panel B, the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year), and Lender-Borrower is the relevant data set. Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. Similarly, borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). We split the sample according to whether the lender is a bank located within the European Union. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country.
Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

banks by resorting to a sample split to compare European and US lenders. In fact, the financial regulatory and institutional framework in place in the country in which banks are located is another potential driver of their reaction to CTR. This is because climate change has only recently become a priority for banking regulators and supervisors, potentially attenuating the impact of single governments climate actions.[25]

Results in Table 10 show that on average, loan margins offered to vulnerable firms in low-CCPI countries before 2016 are relatively more favourable in the case of European banks compared to US banks. The dummy variable Vulnerable yields negative and statistically significant coefficients for the European subsample, while no estimate is significant for the US banks subgroup. This tendency is present even after the Paris Agreement (Vulnerable * Post has negative coefficient estimates for European banks), but is mitigated by the relevance of the climate resilience of the borrower's country. This is not the case for the US banks. The triple interaction yields a (positive) statistically significant coefficients only for the European banks sample, and for one specification only (Column (2)). In that specific case, the economic significance of the results is similar to that found in the previous section: from 2016 onwards, vulnerable borrowers in top-25 CCPI countries were charged on average 52 basis points more[26] than equally vulnerable borrowers located in bottom 75-CCPI countries. Furthermore, during the same period, in top- 25 CCPI countries, vulnerable borrowers paid prices 13 basis points higher,[27] on average, than those applied to non-vulnerable borrowers: a result that mirrors even in magnitude the one related to Table 6.

[25]For instance, in 2018, the European Commission Action Plan on financing sustainable growth (COM/2018/097) outlined the role the financial sector should play in promoting and accelerating the green transition in Europe. It was only in 2020 that the ECB published its Guide on climate-related and environmental risks, sharing its supervisory expectations regarding banks' risk management and disclosure in this area (see ECB 2020).

[26]The result is obtained by combining the estimated coefficients reported in Column (2) as follows: (−4.966 + 12.18 + 24.13 + 12.05-42.82-21.03 + 36.36)-(−4.966 + 12.05-42.82) = 51.64.

[27]The result is obtained by combining the estimated coefficients reported in Column (2) as follows: ((−4.966 + 12.18 + 24.13 + 12.05-42.82-21.03 + 36.36)-(12.18 + 12.05-21.03) = 12.70.

On the credit supply side, our findings, although in line with the main analysis for both subsamples, underscore a statistical difference in the behavior of European banks vis-à-vis US banks when Loan Amount is considered (Table 11, Panel A). The estimated coefficients for the triple interaction have a stronger statistical significance for European banks and are greater in magnitude compared to their US counterparts. This pattern holds also true for the Vulnerable-Post Paris and High CCPI-Post Paris interactions. When replicating this sample split with Loan Share as dependent variable (Table 11, Panel B), we find no significant difference across the two subsamples, pointing to a reallocation effect for banks in both groups.

Lenders' Green attitude

Literature shows that the lenders' ethical attitudes are also relevant determinants for loan pricing decisions in relation to risks derived from sources that are not merely financial, such as CTR (for instance, Degryse et al. 2023, Delis et al. 2017). Specifically, we investigate whether the banks' green attitude influences their lending behaviour, in particular in the direction of reacting more strongly when higher CTR manifest themselves. Literature on this topic is not unanimous. On the one hand, there is evidence that green lenders tend to penalize highly-polluting or vulnerable borrowers (e.g., Degryse et al. 2023, Delis et al. 2021). Others, such as Ehlers et al. (2022), find that the pricing of CTR does not exhibit significant differences when the loans are arranged by lead banks with "greener" attitudes, consistently with a competitive loan market in which climate change transition risks are priced by all banks.

To contribute to the debate, in Tables 12 and 13 we split the sample according to the "greenness" of the bank. In line with previous studies (e.g., Degryse et al. 2023, Delis et al. 2021), we label as "Green" the banks that, in each year t, are already members of the United Nations Environment Programme Finance Initiative (UNEP FI). Therefore, the dummy GreenBank is attributed value 1 for each year that follows the lenders' joining of the Initiative.[28]

All in all, we find only limited evidence of a different response to increasing CTR in green as opposed to non-green banks. In terms of loan pricing (Table 12), we do not detect significant effects for either subsample. The analysis on credit supply yields statistically significant estimated coefficients, which assume the same sign as our baseline results. In the Loan Amount case (Table 13, Panel A), both subsamples reflect the overall tendencies highlighted for the main analyses, displaying positive coefficients for the triple interaction terms. The Green bank group shows stronger statistical significance in the estimated coefficients (Columns (1) and (5)).

The analysis concerning Loan Share (Table 13, Panel B) does not underscore significant discrepancies in terms of estimated coefficients for the triple interaction, which are negative as in baseline results. In contrast, the estimated coefficient for the Vulnerable*Post Paris interaction shows that Green banks have, on average, reduced the weight of vulnerable borrowers in their share of newly-issued loans in the years following the Paris Agreement, independently of the climate resilience of the borrowers' country, while Non-Green banks show positive and statistically significant coefficients for that interaction for top-25 percent vulnerable borrowers. This is the only remarkable difference between the two bank groups in response to CTR, suggesting that, in the post-Paris period, banks that commit to green or sustainability standards are, on average, more likely to reduce the weight of loans to CTR-vulnerable borrowers compared to noncommitted banks. In unreported results, we replicate the analysis identifying as "Green" banks that, at t-1, were among the signatories of another set of relevant standards, the Equator Principles.[29] Results are consistent with those in Tables 12 and 13.

4.3.2 | Robustness checks

We evaluate the robustness of our results by augmenting our main specifications with additional time-varying controls, fixed effects, and employing alternative measures of CTR.

[28]The employed "GreenBank" definition returns 2172 observations in the Green group for the Facility-Lead Arranger data set (which corresponds to 43% of the sample), and 1726 observations in the Green group for the Lender-Borrower data set (37% of the sample).

[29]The list of signatories as well as the date of their joining can be accessed at https://equator-principles.com/.

TABLE 12 Loan margin. CTR and bank greenness.

	Green banks				Non-Green banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Loan margin (bps)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerable	−42.99***	−20.53*	−50.61***	−46.06***	−17.30*	−10.69	−17.65*	−12.17
	(12.28)	(10.95)	(11.68)	(12.45)	(9.605)	(8.573)	(9.545)	(7.441)
High CCPI	−21.44**	2.603	2.071	26.97**	−1.660	3.313	7.728	11.61
	(9.489)	(10.66)	(7.051)	(11.92)	(9.556)	(10.66)	(9.367)	(11.70)
Vulnerable * High CCPI	41.58**	14.98	−12.77	−43.03*	11.84	−7.697	−0.913	−24.96
	(17.08)	(16.77)	(18.84)	(22.13)	(11.49)	(12.94)	(11.95)	(17.31)
Post Paris	−13.38	−5.691	−8.583	−12.81*	−2.398	−1.310	0.288	−3.509
	(8.645)	(10.57)	(7.249)	(6.873)	(6.236)	(6.418)	(5.545)	(5.539)
Vulnerable * Post Paris	7.606	−14.54	−22.30	−20.49	−6.539	−16.18*	−17.21*	−20.40**
	(13.70)	(13.83)	(16.75)	(15.08)	(9.102)	(9.689)	(8.735)	(9.606)
High CCPI * Post Paris	15.78	4.407	−2.182	6.976	0.376	−1.896	−9.932	2.641
	(11.51)	(15.02)	(8.115)	(12.07)	(11.72)	(12.46)	(14.13)	(10.76)
Vulnerable * High CCPI * Post Paris	−15.66	44.07*	22.98	37.36	−12.40	26.83	0.435	16.75
	(26.21)	(21.74)	(39.11)	(39.32)	(10.91)	(16.57)	(21.24)	(24.01)
Observations	1,346	1,346	1,346	1,346	1,678	1,678	1,678	1,678
R-squared	0.551	0.555	0.571	0.577	0.586	0.587	0.589	0.591
Adjusted R-Squared	0.520	0.525	0.541	0.548	0.562	0.562	0.565	0.566

Note: The table presents OLS estimation results. The dependent variable is loan margin (in basis points); the Facility-Lead Arranger configuration is the reference data set. Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. Similarly, borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). The sample is split according to the time-varying dummy Green Bank, which, at each period t, takes value 1 if bank j had joined the UNEPFI standards at t-1 or earlier. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country. Standard errors are clustered at bank-level. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

To account for heterogeneity in legal, political and macroeconomic frameworks, which may influence, among other aspects, attitudes towards climate change and perceptions of climate-related risks, we include fixed effects for the country of the borrowing firms. We capture the different interest rate environments across the countries in which banks are located by controlling for the change in the monetary policy rate. Following Elliot et al. (2023), we consider the (annualised) central bank rate or, where not available, either the money market interest rate or the short-term government bond rate. Table 14 and Table 15 show that our main results are robust to the inclusion of borrower's country fixed effects and of monetary policy rates controls.

TABLE 13 Credit supply. CTR and bank greenness.

	Green banks				Non-Green banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
Panel A:	**CCPI: top50**	**CCPI: top25**	**CCPI: top50**	**CCPI: top25**	**CCPI: top50**	**CCPI: top25**	**CCPI: top50**	**CCPI: top25**
Loan amount (log)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Vulnerable	0.368***	0.219**	−0.0116	−0.142	0.291***	0.292***	0.118	0.187*
	(0.120)	(0.0823)	(0.200)	(0.0879)	(0.0904)	(0.0989)	(0.106)	(0.0957)
High CCPI	0.884***	0.778***	0.624***	0.449***	0.832***	0.571***	0.605***	0.324***
	(0.148)	(0.0641)	(0.181)	(0.109)	(0.121)	(0.126)	(0.105)	(0.111)
Vulnerable * High CCPI	−0.722***	−0.606***	−0.260	0.0296	−0.304	−0.174	0.154	0.342*
	(0.123)	(0.0895)	(0.230)	(0.170)	(0.213)	(0.175)	(0.145)	(0.175)
Post Paris	0.987***	0.752***	0.619***	0.500***	0.483***	0.293***	0.334***	0.154
	(0.264)	(0.132)	(0.204)	(0.118)	(0.0850)	(0.0752)	(0.124)	(0.113)
Vulnerable * Post Paris	−1.060***	−0.708***	−0.676*	−0.622**	−0.384***	−0.310***	−0.193	−0.188
	(0.284)	(0.179)	(0.366)	(0.292)	(0.133)	(0.115)	(0.225)	(0.250)
High CCPI * Post Paris	−1.057***	−0.825***	−0.621***	−0.610***	−0.521***	−0.159	−0.375**	−0.0226
	(0.261)	(0.167)	(0.159)	(0.112)	(0.116)	(0.120)	(0.161)	(0.142)
Vulnerable * High CCPI * Post Paris	1.291***	0.471	0.809*	0.703	0.383*	0.112	0.472	0.00442
	(0.390)	(0.299)	(0.447)	(0.620)	(0.205)	(0.184)	(0.315)	(0.442)
Observations	1,346	1,346	1,346	1,346	1,678	1,678	1,678	1,678

(Continues)

TABLE 13 (Continued)

Panel A:	Green banks				Non-Green banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Loan amount (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R-squared	0.726	0.720	0.719	0.717	0.643	0.637	0.643	0.637
Adjusted R-Squared	0.707	0.701	0.699	0.698	0.621	0.615	0.622	0.616

Panel B	Green banks				Non-Green banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	Top50 CCPI	Top25 CCPI	Top50 CCPI	Top25 CCPI	Top50 CCPI	Top25 CCPI	Top50 CCPI	Top25 CCPI
Loan share (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerable	0.730	0.783	2.130**	2.213**	1.246	1.375*	1.151	1.435**
	(0.808)	(0.849)	(0.889)	(0.961)	(0.809)	(0.786)	(0.752)	(0.708)
High CCPI	1.628	2.148	1.181	1.928	−0.855	0.556	−1.402	0.620
	(1.356)	(1.710)	(0.810)	(1.153)	(1.287)	(1.100)	(1.116)	(1.294)
Vulnerable * High CCPI	2.411	6.342**	7.439***	17.96***	3.318**	8.123***	9.019***	22.73***
	(1.610)	(2.672)	(2.479)	(5.104)	(1.458)	(2.973)	(2.012)	(4.577)
Post Paris	2.214***	1.954**	1.607**	2.011**	−0.00166	0.0914	−0.972*	−0.615
	(0.792)	(0.809)	(0.753)	(0.774)	(0.488)	(0.489)	(0.525)	(0.518)
Vulnerable * Post Paris	−0.976	0.0865	−0.142	−0.187	−0.301	0.209	2.062**	2.205**
	(1.184)	(1.142)	(0.961)	(1.071)	(0.899)	(0.897)	(0.930)	(0.968)
High CCPI * Post Paris	2.537	2.085	3.646***	0.177	10.31***	8.941***	10.33***	6.340**
	(1.533)	(1.739)	(1.248)	(1.346)	(2.974)	(3.244)	(2.141)	(2.657)
Vulnerable * High CCPI * Post Paris	−0.0335	−8.928***	−6.210*	−17.70***	−5.461	−17.57***	−12.45***	−31.35***
	(2.478)	(2.962)	(3.297)	(5.021)	(3.840)	(4.568)	(4.178)	(5.986)

TABLE 13 (Continued)

Panel B	Green banks				Non-Green banks			
	Vulnerable: top50		Vulnerable: top25		Vulnerable: top50		Vulnerable: top25	
	Top50 CCPI	Top25 CCPI	Top50 CCPI	Top25 CCPI	Top50 CCPI	Top25 CCPI	Top50 CCPI	Top25 CCPI
Loan share (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	1,598	1,598	1,598	1,598	2,780	2,780	2,780	2,780
R-squared	0.435	0.437	0.446	0.457	0.311	0.312	0.319	0.325
Adjusted R-Squared	0.421	0.424	0.432	0.441	0.302	0.304	0.307	0.312

Note: The table presents OLS estimation results. In Panel A, the dependent variable is the logarithm of loan amount (converted in thousands USD); the Facility-Lead Arranger configuration is the data set of reference. In Panel B, the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year). The reference data set is Lender-Borrower. Vulnerable borrowers are defined as having CO2 emissions above a certain threshold in a given year: the two distinct definitions employed are based on the median and on the 75th percentile as reference values. Similarly, borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). The sample is split according to the time-varying dummy Green Bank, which, at each period t, takes value 1 if bank j had joined the UNEPFI standards at t-1 or earlier. All specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, and GDP controls for the borrowers' country. Standard errors are clustered at bank-level.

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 14 Loan pricing. Continuous analysis with country fixed effects and monetary interest rate control.

	Dep. Var.: Loan margin (bps)			
	Time FE		Post dummy: 2016, 2017, 2018	
	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI
Panel A: Loan pricing	(1)	(2)	(3)	(4)
CO2	−1.38e-05	0.00103	7.82e-05	0.00183*
	(0.000104)	(0.000653)	(0.000108)	(0.000945)
CCPI		0.207		−0.803
		(0.159)		(0.500)
CO2 * CCPI		−1.80e-05		−3.04e-05*
		(1.16e-05)		(1.64e-05)
Post			−1.788	−50.39**
			(3.444)	(23.97)
CO2 * Post			−0.000366**	−0.00205
			(0.000153)	(0.00163)
CCPI * Post				0.864**
				(0.403)
CO2 * CCPI * Post				2.88e-05
				(2.77e-05)
Δ Monetary rate	−1.043	−6.170	−5.994	−5.201
	(4.658)	(5.064)	(5.059)	(5.029)
Observations	2,368	2,368	2,368	2,368
R-squared	0.688	0.680	0.681	0.683

TABLE 14 (Continued)

	Dep. Var.: Loan margin (bps)			
	Time FE		Post dummy: 2016, 2017, 2018	
	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI
Panel A: Loan pricing	(1)	(2)	(3)	(4)
Adjusted R-Squared	0.653	0.645	0.646	0.648
Year FE	Yes	Yes	No	No

	Dep. Var.: Loan amount (log)				Dep. Var.: Loan share (%)			
	Time FE		Post dummy: 2016, 2017, 2018		Time FE		Post dummy: 2016, 2017, 2018	
Panel B: Credit supply	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CO2	1.24e-06	−1.41e-05	1.83e-06	−3.69e-06	5.35e-05***	1.05e-05	6.93e-05***	−0.000158
	(2.34e-06)	(1.47e-05)	(2.47e-06)	(1.09e-05)	(1.24e-05)	(0.000125)	(1.43e-05)	(0.000164)
CCPI		0.00197		0.0216***		0.0340		0.0286
		(0.00399)		(0.00545)		(0.0227)		(0.0451)
CO2 * CCPI		2.66e-07		9.81e-08		7.52e-07		4.28e-06
		(2.48e-07)		(1.70e-07)		(2.17e-06)		(2.97e-06)
Post			0.164***	1.363***			1.051***	−0.441
			(0.0483)	(0.279)			(0.400)	(2.586)
CO2 * Post			−2.94e-06**	−1.18e-05			−4.19e-05***	0.000237
			(1.30e-06)	(2.28e-05)			(1.05e-05)	(0.000168)
CCPI * Post				−0.0208***				0.0324
				(0.00465)				(0.0476)

(Continues)

TABLE 14 (Continued)

Panel B: Credit supply	Dep. Var.: Loan amount (log)				Dep. Var.: Loan share (%)			
	Time FE		Post dummy: 2016, 2017, 2018		Time FE		Post dummy: 2016, 2017, 2018	
	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI	CO2 Emissions	CO2 Emissions * CCPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CO2 * CCPI * Post				1.56e-07				−5.26e-06*
				(3.79e-07)				(3.16e-06)
Δ Monetary rate	0.0305	0.0280	0.0148	−0.00332	−0.0425	0.185	0.153	0.141
	(0.0434)	(0.0426)	(0.0356)	(0.0364)	(0.279)	(0.247)	(0.249)	(0.243)
Observations	2,368	2,368	2,368	2,368	3,697	3,697	3,697	3,697
R-squared	0.702	0.703	0.698	0.701	0.601	0.599	0.601	0.602
Adjusted R-Squared	0.670	0.670	0.665	0.668	0.570	0.569	0.571	0.572
Year FE	Yes	Yes	No	No	Yes	Yes	No	No

Note: The table presents OLS estimation results. In Panel A, the dependent variable is Loan Margin (in bps). As for Panel B, in columns (1)-(4), the dependent variable is the logarithm of loan amount (converted in thousands USD). The data set of reference is the Facility-Lead Arranger. In columns (5)-(8), the dependent variable is Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year, in percentage points). The data set of reference is the Lender-Borrower configuration. The main regressor is CO2 (total carbon emissions of firm i in year t, in thousands of tonnes); it is interacted with firm's country CCPI. The dummy variable Post takes value 1 for the years 2016, 2017, 2018, and zero otherwise. All specifications include loan, bank, firm and firm's country time-varying controls, along with loan purpose and loan type fixed effects, firms' industry fixed effects, and relevant monetary rates for lenders. Fixed effects for the bank and for the country of the borrower are also included. Year fixed effects are employed for specifications that do not include the dummy variable Post. Standard errors are clustered at bank level.

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 15 Loan pricing and credit supply. Binary analysis with country fixed effects and monetary rate control.

	Dep. Var.: Loan margin (bps)			
	Vulnerable: top50		Vulnerable: top50	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Panel A: Loan pricing	**(1)**	**(2)**	**(3)**	**(4)**
Vulnerable	−9.831	−1.766	9.678	5.865
	(11.76)	(9.808)	(9.055)	(6.671)
High CCPI	−36.52***	4.271	−16.92	65.21***
	(10.64)	(18.41)	(10.93)	(23.03)
Vulnerable * High CCPI	15.62	−11.07	−31.63***	−83.25***
	(12.12)	(12.38)	(11.64)	(16.62)
Post	−12.41**	−4.099	−5.882	0.403
	(5.379)	(5.920)	(5.473)	(6.455)
Vulnerable * Post	−1.715	−7.305	−31.03**	−27.92**
	(8.832)	(8.145)	(12.81)	(12.29)
High CCPI * Post	16.36**	3.607	8.300	−2.977
	(7.677)	(9.359)	(8.589)	(11.54)
Vulnerable * High CCPI * Post	−1.811	22.89*	4.480	42.21
	(11.20)	(13.56)	(30.66)	(33.22)
Δ Monetary rate	2,368	2,368	2,368	2,368
	0.682	0.681	0.685	0.689

(Continues)

TABLE 15 (Continued)

Panel A: Loan pricing	Dep. Var.: Loan margin (bps) Vulnerable: top50 CCPI: top50 (1)	Vulnerable: top50 CCPI: top25 (2)	Vulnerable: top50 CCPI: top50 (3)	Vulnerable: top50 CCPI: top25 (4)
Observations	0.647	0.645	0.650	0.654
R-squared	−9.831	−1.766	9.678	5.865
Adjusted R-Squared	(11.76)	(9.808)	(9.055)	(6.671)

	Dep. Var.: Loan amount (log)				Dep. Var.: Loan share (%)			
	Vulnerable: top50		Vulnerable: top50		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
Panel B: Credit supply	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerable	0.318**	0.189	0.127	0.0298	0.249	0.209	2.193***	2.288***
	(0.135)	(0.144)	(0.0788)	(0.0971)	(0.420)	(0.438)	(0.520)	(0.525)
High CCPI	1.023***	0.490***	0.771***	0.109	1.769**	9.212***	1.098	7.460**
	(0.134)	(0.166)	(0.113)	(0.145)	(0.888)	(2.860)	(0.734)	(3.185)
Vulnerable * High CCPI	−0.639***	−0.469***	−0.285**	−0.0748	−0.471	0.411	2.161	3.071
	(0.207)	(0.168)	(0.128)	(0.155)	(1.043)	(1.357)	(1.320)	(3.240)
Post	0.638***	0.533***	0.466***	0.413***	0.989**	0.825*	0.599	0.608
	(0.0977)	(0.0830)	(0.106)	(0.0926)	(0.459)	(0.459)	(0.498)	(0.470)
Vulnerable * Post	−0.629***	−0.489***	−0.548***	−0.581***	−0.485	−0.377	0.281	−0.0130
	(0.118)	(0.111)	(0.183)	(0.189)	(0.599)	(0.610)	(0.547)	(0.545)
High CCPI * Post	−0.699***	−0.636***	−0.397***	−0.533***	0.307	0.588	0.900	−0.0875
	(0.125)	(0.131)	(0.113)	(0.114)	(2.198)	(1.921)	(1.625)	(1.463)

TABLE 15 (Continued)

Panel B: Credit supply	Dep. Var.: Loan amount (log)				Dep. Var.: Loan share (%)			
	Vulnerable: top50		Vulnerable: top50		Vulnerable: top50		Vulnerable: top25	
	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25	CCPI: top50	CCPI: top25
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerable * High CCPI * Post	0.978***	0.436***	0.709**	0.935***	0.532	−1.888	−4.579**	−4.907
	(0.162)	(0.142)	(0.289)	(0.305)	(2.166)	(2.382)	(2.256)	(3.392)
Δ Monetary rate	2,368	2,368	2,368	2,368	3,661	3,661	3,661	3,661
	0.711	0.703	0.708	0.705	0.596	0.597	0.599	0.601
Observations	0.679	0.671	0.676	0.673	0.566	0.567	0.569	0.571
R-squared	0.318**	0.189	0.127	0.0298	0.249	0.209	2.193***	2.288***
Adjusted R-Squared	(0.135)	(0.144)	(0.0788)	(0.0971)	(0.420)	(0.438)	(0.520)	(0.525)

Note: The table presents OLS estimation results. In Panel A, the dependent variables is Loan Margin (in bps). Columns (1)-(4) in Panel B report results relative to Loan Amount (in log) as dependent variable. In both cases, the data set of reference is the Facility-Lead Arranger configuration and all specifications include loan, firm and bank controls, loan purpose and loan type fixed effects, firms' industry fixed effects, GDP controls for the borrowers' country, monetary interest rates in bank's country, as well as fixed effects for the bank and the borrowers' country.

Columns (5)-(8) in Panel B shows results concerning Loan Share (total syndicated lending from bank j to borrower i in a given year as a share of bank j's total gross loans in that year) as dependent variable. The reference data set is Lender-Borrower and all specifications include loan, firm and bank controls, firms' industry fixed effects, GDP controls for the borrowers' country, monetary interest rates in bank's country, as well as fixed effects for the bank and the borrowers' country.

Borrowers are identified as vulnerable if their CO_2 emissions at time t exceed a given threshold (either the median or the 75th percentile) with respect to the carbon emissions of their peers (firms operating in the same 2-digit industry, in the same country). Borrowers' countries are classified into high climate change-sensitive countries and low climate change-sensitive according to whether their CCPI score in a year falls above a given threshold (either the median or the 75th percentile value of CCPI computed among all countries for which the measure is provided). The dummy Post identifies as "post-period" the years 2016, 2017 and 2018.

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

In unreported results, available upon request, we perform further robustness checks. We replicate the main analyses by including, as additional control variables at the bank level, a measure of the bank's overall exposure to transition risk. We also use an alternative measure of the Loan Share variable, calculated as the total amount of syndicated lending a bank provides to a specific borrower as a percentage of the total syndicated loans (rather than total loans, as in our prefererred variable) in which the bank engages during the year. The results are robust.

We also consider an alternative definition of the time dummy Post identifying the cutoff date as January 1st, 2017 (instead of 2016) and find that the baseline results are confirmed. This suggests that the Paris Agreement, which was ratified on December 12th, 2015 and entered into force on November 4th, 2016, has had a persistent effect on banks' behaviour.

Furthermore, our main results are robust to clustering standard errors by the borrower's country. This alternative clustering may be relevant since the CCPI varies precisely at that level. Our findings are also robust when including loan margin as one of the loan-level control variables in the credit supply analyses. Lastly, we replace our proxy of climate resilience at the country level (namely, Germanwatch's CCPI index), which spans several dimensions relevant to evaluating a country's efforts to combat climate change, with a more focused indicator that specifically measures climate policy stringency in a country, i.e., the OECD's Environmental Policy Stringency indicator. Once again, the results are similar as to those reported in the main tables.

5 | CONCLUSIONS

This work examines bank lending behaviour in a context of increasing climate transition risks. By using a granular sample obtained by merging corporate, lender, and country information to syndicated loans data, we investigate two relevant dimensions for bank lending, namely loan pricing and supply. Our objective is to determine whether banks incorporate climate transition risks into loan pricing and whether they reduce credit, both in terms of loan amount and share of total loans, to borrowers who are more exposed to climate transition risk.

We provide a comprehensive measure of exposure to CTR, considering three important risk drivers: the borrower's carbon emissions, a policy shock represented by the 2015 Paris Agreement, and climate resilience and policy stringency of the country in which borrowers are located.

After controlling for all these factors, we find limited evidence of a pricing effect: banks have charged higher margins to polluting borrowers after the Paris Agreement, particularly in countries that are more aware of climate change issues. We do not find a significant effect when considering credit supply measures.

We also explore nonlinearities by introducing dummy variables for vulnerable borrowers and climate-resilient countries. The results are more pronounced and indicate a nonlinear relationship between loan variables and CTR measures at both the firm level (carbon emissions) and the country level (engagement in climate action). In particular, we find that banks respond to higher climate risk by increasing the cost and the amount of credit to highly polluting firms located in countries with very stringent climate policies. At the same time, the share allocated to these borrowers has decreased, pointing to a reallocation effect within the loan portfolio mix.

We then measure the banks' exposure to CTR by grouping borrowers based on CO2 emission intensity at the industry level. We find that banks have increased both the cost and the amount and share of loans granted to highly polluting industries in the post-Paris Agreement period, with no evidence of reallocation as found in the analysis at the borrower level.

The richness of our data allows us to extend our main analysis and address other relevant questions. We provide evidence that the price effect is more pronounced for European borrowers whereas we do not find discrepancies in credit supply measures. The baseline results concerning loan price and loan amount seem to be driven by European banks, whereas we detect only limited evidence that banks adhering to green standards are incorporating increasing CTR.

Overall, we find evidence supporting the incorporation of climate transition risks by banks, especially in countries more engaged in addressing climate change issues since the Paris Agreement. However, banks' responses to increased CTR are not uniform, and the relations among relevant variables are not linear. In terms of policy implications, our findings underscore the importance of comprehensively measuring firms' exposure to CTR, considering both idiosyncratic and country-specific factors. Similarly, banks' exposure to climate-related risk needs to be assessed at both firm and industry level, as evidence on banks' reaction to CTR may vary depending on the proxy used.

CONFLICTS OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

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REFERENCES

Alogoskoufis, S., Dunz, N., Emambakhsh, T., Hennig, T., Michiel Kaijser, C. K., Munoz, M. A., and C. Salleo, 2021, ECB economy-wide climate stress test. Methodology and results, *Occasional Paper Series No. 281*.

Antoniou, F., Delis, M. D., Ongena, S., and C. Tsoumas, 2020, Pollution permits and financing costs, *CEPR Discussion Paper DP15517*.

Baudino, P. and J.-P. Svoronos, 2021, Stress-testing banks for climate change – a comparison of practices, *FSI Insights on policy implementation No. 34, July 2021*.

Ben-David, I., Jang, Y., Kleimeier, S. and M. Viehs, 2021, Exporting pollution: where do multinational firms emit CO_2? *Economic Policy 36*, 107, 377–437.

Benincasa, E., Kabas, G., and S. Ongena, 2021, There is No Planet B, but for banks there are Countries B to Z: Domestic climate policy and cross-border bank lending, *CEPR Discussion Paper DP16665*.

Berg, F., Kölbel, J. F., and R. Rigobon, 2022, Aggregate Confusion: The Divergence of ESG Ratings, *Review of Finance 26*(6), 1315–1344.

BIS, 2021a, Climate-related risks drivers and their transmission channels. *Basel Committee on Banking Supervision - Bank of International Settlements*, https://www.bis.org/bcbs/publ/d517.pdf

BIS, 2021b, Climate-related financial risks – measurement methodologies, *Basel Committee on Banking Supervision - Bank of International Settlements*, https://www.bis.org/bcbs/publ/d518.pdf

Bolton, P. and M. Kacperczyk, 2023, Global pricing of carbon-transition risks. *The Journal of Finance*, *78*(6), 3051–3757.

Bolton, P., Despres, M., Pereira da Silva, L. A., Samama, F., and R. Svartzman, 2020, The green swan: Central banking and financial stability in the age of climate change, *Bank of International Settlements - Bank of France*.

Brambor, T. C., Clark, W. R., and M. Golder, 2006. Understanding interaction models: improving empirical analyses. *Political Analysis 14*(1), 63–82.

Carney, M., 2015, Breaking the Tragedy of the Horizon – climate change and financial, *Speech given at Lloyd's of London, 29 September 2015*.

Carney, M., 2021, Value(s): Building a better world for all, William Collins.

Chatterji, A. K., Durand, R., Levine, D., and S. Touboul, 2016, Do ratings of firms converge? implications, *Strategic Management Journal*, *37*, 1597–1614.

Cifuentes-Faura, J., 2022, European Union policies and their role in combating climate change over the years, Air Quality, Atmosphere & Health volume 15, pages 1333–1340.

De Haas, R. D., and A. Popov, 2019, Finance and carbon emissions, *ECB Working Paper No. 2318*.

Degryse, H., Goncharenko, R., Theunisz, C., and T. Vadasz, 2023, When green meets green, *Journal of Corporate Finance*, *78*(102355), 1–25.

Degryse, H., Roukny, T., and J. Tielens, 2020, Banking barriers to the green economy, *National Bank of Belgium Working Paper N. 391*.

Delis, M., de Greiff, K., Iosifidi, M., and S. Ongena, 2021, Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans, *Swiss Finance Institute Research Paper Series No. 18–10*.

Delis, M., Hasan, I., and S. Ongena, 2017, Democracy and credit: 'Democracy doesn't come cheap' but at least credit to its corporations will be, *Swiss Finance Institute Research Paper Series No. 17-14*.

Doerr, S. and P. Schaz, 2021, Geographic diversification and bank lending during crises, *Journal of Financial Economics*, *140*(3), 768–788.

Donefer, C., 2023, State ESG laws in 2023: The landscape fractures, *Thomson Reuters*, https://www.thomsonreuters.com/en-us/posts/esg/state-laws/
ECB, 2020, *Guide on climate-related and environmental risks: Supervisory expectations relating to risk management and disclosure*.
ECB, 2021a, Climate-related risk and financial stability, *ECB/ESRB Project Team on climate risk monitoring*, July 2021.
ECB, 2021b, Climate-related risk and financial stability - Data supplement, *ECB - ESRB Project Team on climate risk monitoring*, July 2021.
Ehlers, T., Packer, F., and K. de Greiff, 2022, The pricing of carbon risk in syndicated loans: Which risks are priced and why? *Journal of Banking and Finance*, *136*(106180), 1–13.
Elliot, D., Meisenzhal, R. R., and J. Peydró, 2023, Nonbank lenders as global shock absorbers: evidence from US Monetary Policy Spillovers, *Bank of England*, Staff Working Paper No. 1,012.
Erragragui, E., 2018, Do creditors price firms' environmental, social and governance risks? *Research in International Business and Finance*, *45*, 197–207.
ESRB, 2020, Positively green: Measuring climate change risks to financial stability. *European System Risk Board*, June 2020, https://www.esrb.europa.eu/pub/pdf/reports/esrb.report200608_on_Positively_green_-_Measuring_climate_change_risks_to_financial_stability~d903a83690.en.pdf?c5d033aa3c648ca0623f5a2306931e26
Fard, A., Javadi, S., and I. Kim, 2020, Environmental regulation and the cost of bank loans: international evidence, *Journal of Financial Stability*, *51*(100797), 1–17.
Fatica, S., Panzica, R., and Rancan, M., 2021, The pricing of Green bonds: are financial institutions special? *Journal of Financial Stability*, *54*(100873), 1–20.
FSB, 2020, *The implications of climate change for financial stability, Financial Stability Board, November 2020*, https://www.fsb.org/wp-content/uploads/P231120.pdf
FSB, 2021, The availability of data with which to monitor and assess climate-related risks to financial stability, *Financial Stability Board, July 2021*, https://www.fsb.org/wp-content/uploads/P070721-3.pdf
Goss, A., and G. S. Roberts, 2011, The impact of corporate social responsibility on the cost of bank loans, *Journal of Banking and Finance*, *35*, 1794–1810.
Hauptmann, C., 2017, Corporate sustainability performance and bank loan pricing: it pays to be good, but only when banks are too, *Saïd Business School Research Papers*.
Hong, H., and M. Kacperczyk, 2009, The price of sin: the effects of social norms on markets, *Journal of Financial Economics*, *93*, 15–36.
Houston, J. F., and Shan, H. 2022, Corporate ESG profiles and banking relationships, *Review of Financial Studies*, *35*(7), 3373–3417.
Ivanov, I. T., Kruttli, M. S., and S. W. Watugala, 2023, Banking on carbon: corporate lending and Cap-and-Trade policy, SSRN Working Paper Series 3650447.
Ivashina, V., 2005, Structure and pricing of syndicated loans, *The New York City Area Conference on Financial Intermediation*, 18 November 2005.
Ivashina, V., 2009, Asymmetric information effects on loan spreads, *Journal of Financial Economics*, *92*, 300–319.
Kacperczyk, M., and J. L. Peydró, 2021, Carbon Emissions and the Bank-Lending Channel, *Discussion Paper DP16778*.
Mueller, I., and E. Sfrappini, 2022, Climate Change-Related Regulatory Risks and Bank Lending, *ECB Working Paper Series* (2670/June 2022).
NGFS, 2019, A call for action: Climate change as a source of financial risk. *Network for Greening the Financial System First Comprehensive Report*, https://www.ngfs.net/sites/default/files/medias/documents/ngfs_first_comprehensive_report_-_17042019_0.pdf
Reghezza, A., Altunbas, Y., Marques-Ibanez, D., Rodriguez d'Acri, C., and M. Spaggiari, 2021, Do banks fuel climate change? *ECB Working Paper Series N. 2550*.
Selin, H. and S. VanDeveer, 2015, Broader, deeper and greener: european union environmental politics, policies, and outcomes, *Annual Review of Environment and Resources*, *40*, 309–335.
Sharfman, M. P., and C. S. Fernando, 2008, Environmental risk management and the cost of capital, *Strategic Management Journal*, *29*, 569–592.

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APPENDIX

See Table Table A1 and A2

TABLE A1 Borrowers by country and industry.

Panel A: Country	Facility-Lead Arranger Frequency	Facility-Lead Arranger Percent	Lender-Borrower Frequency	Lender-Borrower Percent
Australia	197	3.88	309	6.63
Austria	40	0.79	23	0.49
Belgium	105	2.07	12	0.26
Brazil	25	0.49	49	1.05
Canada	133	2.62	24	0.51
China	25	0.49	30	0.64
Finland	2	0.04	0	0
France	286	5.63	88	1.89
Germany	465	9.15	42	0.9
Greece	3	0.06	5	0.11
Hong Kong	52	1.02	59	1.27
India	44	0.87	53	1.14
Indonesia	4	0.08	0	0
Ireland	76	1.5	0	0
Italy	184	3.62	36	0.77
Japan	56	1.1	20	0.43
Luxembourg	59	1.16	7	0.15
Mexico	2	0.04	0	0
Netherlands	19	0.37	9	0.19
Norway	11	0.22	0	0
Poland	12	0.24	0	0
Russian Federation	52	1.02	3	0.06
Singapore	15	0.3	8	0.17
South Africa	105	2.07	11	0.24
South Korea	24	0.47	21	0.45
Spain	418	8.23	242	5.19
Sweden	38	0.75	41	0.88
Switzerland	33	0.65	4	0.09
Taiwan	447	8.8	416	8.92
Thailand	6	0.12	1	0.02

(Continues)

TABLE A1 (Continued)

Panel A: Country	Facility-Lead Arranger Frequency	Percent	Lender-Borrower Frequency	Percent
Turkey	24	0.47	0	0
United Kingdom	842	16.57	165	3.54
United States	1,278	25.15	2,984	64.01
Total	**5,082**	**100**	**4662**	**100**
Panel B: SIC Industry	**Frequency**	**Percent**	**Frequency**	**Percent**
Agriculture, Forestry and Fishing	8	0.16	10	0.21
Mining	735	14.46	543	11.65
Construction	246	4.84	82	1.76
Transportation, Communications, Electric, Gas and Sanitary service	928	18.26	1001	21.47
Wholesale Trade	151	2.97	95	2.04
Retail Trade	263	5.18	232	4.98
Finance, Insurance and Real Estate	48	0.94	25	0.54
Services	534	10.51	378	8.11
Public Administration	2	0.04	0	0
Total	**5082**	**100**	**4662**	**100**

TABLE A2 Test for differences in means by vulnerability group.

Variables	Vulnerable Mean	SD	Non-Vulnerable Mean	SD	t-test Difference	S.E.
Panel A: Facility-Lead Arranger data set						
Loan margin (bps)	130.842	93.697	158.361	98.637	27.519***	(10.150)
Loan amount (log)	7.069	1.21	6.298	1.495	−0.771***	(−20.012)
Loan amount (thousand USD)	2450.033	4344.443	1541.318	3482.574	−908.715***	(−8.271)
nLenders	9.695	8.14	5.792	5.249	−3.902***	(−20.568)
Secured	0.135	0.342	0.176	0.381	0.041***	(4.038)
Maturity (months)	50.909	22.991	52.915	24.393	2.006**	(3.002)
Performance Pricing	0.229	0.42	0.191	0.393	−0.039***	(−3.375)
Covenants	0.174	0.379	0.339	0.473	0.165***	(13.573)
Bank's ROA	0.513	0.595	0.54	0.637	0.028	(1.322)
Bank's E/TA	6.76	3.653	7.16	3.586	0.400***	(3.346)
Bank's total assets (log)	13.289	1.573	13.182	1.657	−0.106*	(−1.985)
Bank's total assets	1100950	821663.5	1071566	820936.4	−29384.197	(−1.082)
Bank's Tier1 ratio	13.019	2.93	13.111	3.276	0.092	(0.833)

TABLE A2 (Continued)

Variables	Vulnerable Mean	Vulnerable SD	Non-Vulnerable Mean	Non-Vulnerable SD	t-test Difference	t-test S.E.
Bank's Cost-to-Income Ratio	61.893	16.134	63.097	15.873	1.204*	(2.229)
Bank's NLP to Total Loans	2.717	2.763	2.714	2.604	−0.003	(−0.035)
GreenBank (UNEPFI)	0.444	0.497	0.408	0.492	−0.035*	(−2.534)
Firm's total assets (log)	10.369	1.153	8.771	1.19	−1.598***	(−44.519)
Firm's total assets	58431.3	68050.38	12714.7	16973.65	−45716.606***	(−31.563)
Firm's leverage	0.451	0.137	0.387	0.195	−0.064***	(−12.429)
Firm's ROA	3.734	6.809	5.009	10.018	1.275***	(4.889)
Firm's country GDP growth	2.304	2.927	2.281	1.634	−0.023	(−0.351)
Firm's sales (log)	9.801	1.187	8.31	1.228	−1.491***	(−40.101)
Firm's sales	33683.13	43905.99	8531.099	14262.31	−25152.034***	(−26.244)
CO2 Emissions (thousand tonnes)	17918.79	34920.38	250.092	282.028	−17668.696***	(−26.421)
CO2/Revenue	953.632	2177.343	79.11	179.388	−874.522***	(−20.892)
Firm's country CCPI	54.131	11.182	54.214	12.655	0.083	(0.245)
Vulnerable (top25)	0.528	0.499	0	0	−0.528***	(−55.227)
Vulnerable (top50)	1	0	0	0	−1.000	(.)
High CCPI (top50)	0.496	0.5	0.434	0.496	−0.062***	(−4.445)
High CCPI (top25)	0.267	0.442	0.377	0.485	0.110***	(8.405)
Panel B: Lender-Borrower data set						
Loan Share (% Gross Loans)	8.694	12.744	6.782	10.468	−1.912***	(−5.605)
Loan Share (% Syndicated Loans)	0.128	0.213	0.094	0.183	−0.034***	(−5.813)
(Avg.) Maturity	50.277	12.762	52.09	11.858	1.812***	(4.973)
(Avg.) Margin	126.271	52.194	135.752	55.489	9.481***	(5.877)
Bank's ROA	0.645	0.75	0.714	0.988	0.069*	(2.511)
Bank's E/TA	7.799	3.359	8.24	3.82	0.441***	(4.014)
Bank's total assets (log)	13.099	1.377	12.972	1.44	−0.126**	(−2.991)
Bank's total assets	942348.08	851103.51	887701.51	828677.47	−54646.564*	(−2.189)
Bank's Tier1 ratio	12.689	2.262	12.588	2.485	−0.100	(−1.361)
Bank's Cost-to-Income Ratio	60.43	14.562	60.538	14.959	0.108	(0.243)
GreenBank (UNEPFI)	0.376	0.484	0.362	0.481	−0.014	(−0.951)
Firm's leverage	0.471	0.171	0.408	0.187	−0.063***	(−11.661)
Firm's ROA	3.191	8.128	5.408	6.865	2.217***	(10.045)
Firm's total assets (log)	10.517	1.128	9.201	1.015	−1.316***	(−41.561)
Firm's total assets	68102.909	80109.327	16553.634	20231.274	−51549.275***	(−32.315)

(Continues)

TABLE A2 (Continued)

Variables	Vulnerable Mean	Vulnerable SD	Non-Vulnerable Mean	Non-Vulnerable SD	t-test Difference	t-test S.E.
Firm's CO2 Emissions (thousand tonnes)	14889.3	27721.439	371.453	337.591	−14517.846***	(−27.480)
Firm's CO2/Revenue	986.556	2000.214	68.096	115.376	−918.460***	(−24.040)
Firm's country GDP growth	2.294	1.242	2.357	1.023	0.064	(1.915)
Firm's country CCPI	49.972	9.455	51.041	9.599	1.069***	(3.762)
Vulnerable (top25)	0.548	0.498	0	0	−0.548***	(−57.722)
Vulnerable (top50)	1	0	0	0	−1.000	(.)
High CCPI (top50)	0.130	0.337	0.135	0.342	0.038***	(3.819)
High CCPI (top25)	0.064	0.245	0.089	0.285	−0.010	(−1.229)

Note: Vulnerable borrowers are defined according to the 50th percentile threshold.