Carbon Emissions and the Bank-Lending Channel

Finance Working Paper N° 991/2024
August 2026

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1. Introduction

The battle against global warming is at the forefront of social and policy debates. A fundamental element in addressing climate change is the reduction of carbon emissions, particularly those generated by the private sector, a process commonly referred to as decarbonization. Achieving this objective requires the involvement of a wide range of economic actors, including the financial sector, both through the provision of capital and through disciplinary actions that may facilitate environmental progress (see, e.g., Bolton et al. 2021; Giglio et al. 2021).

The banking sector is of particular importance in this process given its central role in allocating resources to non-financial companies (NFCs), its ability to affect firms through both quantity and price adjustments, and its broad reach across public and private firms as well as developed and emerging markets. While banks may respond more slowly to social and regulatory pressure than capital markets, their lending relationships tend to be more stable, suggesting that conditional on adjustment, their actions may be more persistent. At the same time, the role of banks in decarbonization remains ambiguous. Banks are increasingly under pressure to align their lending with climate objectives, yet they continue to finance substantial carbon-intensive activity.[1] Policymakers and central banks have introduced climate-related guidelines and stress-testing frameworks, and banks have adopted voluntary climate commitments, but whether these developments translate into meaningful changes in credit allocation and firm behavior remains largely unresolved.

This raises several related questions. Do banks discipline high-emission firms by restricting credit and reallocating capital toward greener firms? Do they continue to finance carbon-intensive firms, potentially enabling investments in emission reduction? Or are such commitments largely symbolic? More broadly, do changes in bank lending behavior lead to improvements in firms' environmental performance? These questions are central to ongoing policy discussions (e.g., Carney, 2015; Lagarde, 2019).

[1] Between 2015 and 2024, 65 major banks have, for example, allocated $7.9 trillion into fossil fuel industry, including $467bn into oil, gas, and coal in 2024 alone (16th edition of 2025 Banking on Climate Chaos (BOCC) report).

In this paper, we shed light on these issues using a global sample of firms with heterogeneous carbon emission profiles. We examine how firm-level emissions affect bank lending and, through this channel, financial, real, and environmental outcomes. To capture differences in banks' propensity to adjust lending to carbon-intensive firms, we exploit cross-sectional variation in banks' adoption of climate commitments through the Science Based Targets initiative (SBTi). We focus on an early wave of such commitments, between 2015 and 2018, bringing us closer to a setting in which these commitments reflect genuine intent rather than widespread institutional norms. In our setting, bank commitments constitute shocks to firms with prior lending relationships with these banks. Importantly, even if committing banks change their lending behavior, it is not clear whether firms can substitute toward alternative funding sources, and hence continue emitting and investing. As such, we also analyze the credit supply mechanism via firm- and loan-level data.

Our identification strategy relies on pre-existing lending relationships between firms and banks. We define firm exposure to committing banks based on lending relationships formed prior to our sample period, which mitigates concerns about endogenous matching. The staggered timing of bank commitments allows us to implement a difference-in-differences design comparing firms before and after commitments, depending on their prior exposure to committing banks and their ex-ante carbon footprint.

We find strong and robust evidence that bank commitments affect firms' financing outcomes. Firms with higher Scope 1 emissions and prior relationships with committing banks experience a significant reduction in total debt from *all* financing sources relative to otherwise similar firms without such relationships, while low-emission firms receive relatively more credit. The magnitude is economically meaningful: a one-standard-deviation increase in emissions is associated with a reduction in total debt of approximately 5.5 percent. In contrast, we find no significant effects for Scope 2 or Scope 3 emissions, consistent with the greater observability and attribution of Scope 1 emissions.[2]

[2] The results suggest that the shift in credit away from high-emission firms operates both across and within industries. Consistently, all findings are robust to excluding carbon-intensive sectors such as oil and gas.

We provide further evidence on the financing effect using several tests. We first divide firms' total debt into bank debt and non-bank debt and find that the effects for total debt are almost entirely driven by adjustments in bank debt, which suggests that the differences in lending are a direct consequence of bank decisions rather than they are an outcome of an indirect channel in which banks affect the financial decisions of other market participants. The results survive a battery of robustness tests typical for the difference-in-differences setting. Specifically, we find that firms in both the treatment and control groups follow similar trends prior to commitment episodes. Also, among non-committed firms, effects on bank lending are insignificant in the periods around the commitment events. For committed firms, effects are only significant after their banks commit. We further find that both sets of companies are ex ante similar along several firm-level observables, including their level of emissions conditional on firm size, that is, firms that previously were borrowing from committed versus not committed banks are not different in terms of their level of, for example, CO_2 emissions, or risk, leverage, or revenues. Finally, the results satisfy the test of omitted variables and selection on unobservables based on Altonji et al. (2005) and Oster (2019).

We next examine the mechanisms underlying these results. We consider two hypotheses. One possibility is that risk-averse banks reduce lending to high-emission firms due to higher perceived financial risk. Alternatively, banks may adjust lending for reasons not fully explained by borrower risk, including reputational concerns or stakeholder pressure. To distinguish between these explanations, we perform three tests. First, we directly control in our regressions for measures of credit risk based on firm leverage and stock return volatility. Our effect retains its economic significance after controlling for financial risk, even though financial risk also matters for credit allocation. Second, we examine changes in debt maturity. If bank behavior were primarily driven by climate risk considerations, one would expect an adjustment along maturity dimension, given that such risks are typically medium- to long-term in nature. We find no significant change in maturity choices.

Third, we analyze loan-level data including firm-time fixed effects that control for firm unobservables, including business risk. This loan-level analysis provides a more nuanced view of the bank-lending channel and allows us to separate effects that are driven by syndicated loans only from those that are possibly driven by other lending arrangements. Most relevant, absorbing firm-time fixed effects in our regressions allows us to study lending decisions from committed vs. non-committed banks to the same firm at the same time. This within-firm comparison is our most direct evidence of a bank-driven credit supply effect in our setting. We evaluate the extensive and intensive margins of lending. We find that adjustment through syndicate loans happens along the extensive margin: compared to other banks, committed banks trim their participation in loans to firms with high emissions.[3] At the same time, we do not find a significant result on the intensive margin: committed banks extend their syndicated loans as an in-or-out decision and do not partially cut the quantity of credit within a loan that they participate in. This result is consistent with a supply-side shift in credit away from high-emission firms. We also analyze interest expenses, a proxy for loan prices, as another key margin through which credit supply could operate. Our results suggest that brown firms related to committed banks are penalized by higher prices and at the same time lower volumes. The price effect, however, is economically weaker than the quantity effect, which is consistent with the quantity-based net-zero alignment objectives of bank commitments.

While the increased restrictions to access credit may adversely affect emitting firms, the question is whether such firms' corporate decisions internalize the banking force. To answer this question, we investigate firm-level effects, including environmental and real outcomes. In the first set of tests, we evaluate the impact of bank commitments on firm-level financial and real variables. Our estimates suggest that committed firms with high emissions undergo a process of deleveraging, characterized by shrinking bank debt, investment, and asset size. The real effects are non-linear in that we observe a relatively strong cut (increase) in bank lending and investment to most (least) emitting firms, with mild effects in between these extremes. The results are consistent with predictions coming from models of real and financial decisions by firms facing financial inflexibility (e.g., Bolton et al. 2019).

[3] We also find that committed banks (as compared to non-committed banks) reallocate credit from brown to green firms by controlling for not just firm-time fixed effects but also for bank-time fixed effects, which control for all observed and unobserved bank-level variation, including time-varying bank credit volume.

Even though the above findings suggest that firms do respond to bank pressure, the socially most important question is whether such firms adjust their environmental performance. Affected firms face incentives to become greener to regain financing access, but tighter credit conditions may limit their ability to invest in green technologies. Also, firms may be reluctant to cut their investment in carbon-intensive projects if such projects have higher profit margins.

Despite these financial and real effects, we find no evidence that exposed firms improve their environmental performance. Emissions do not decline in either the short or medium term, and firms do not increase their adoption of formal climate commitments. At the same time, affected firms increase profitability, suggesting that they respond by cutting lower-return or longer-horizon investments rather than undertaking costly emission-reduction activities.

We further find that committed firms with higher emissions significantly improve their environmental MSCI *E*-scores, primarily through enhanced disclosure and communication rather than through increased environmental investment. Since such communication efforts need not lead to any changes in real emissions or plans to reduce them, they are consistent with a form of greenwashing by the affected companies. Importantly, committed banks do not appear to treat these improvements as credible, as they continue to reduce lending to such firms, and in some cases do so more strongly for firms making formal commitments.

Contribution to the literature

Our paper contributes to the growing literature on climate finance. A large body of work studies how climate risk is priced in financial markets, documenting that firms with higher carbon exposure face higher required returns and lower valuations, particularly during periods of heightened climate concern (e.g., Bolton and Kacperczyk, 2021, 2023, 2026; Choi et al. 2020; Engle et al. 2020). Related evidence shows that corporate bonds of firms with greater exposure to climate risk earn lower ex-post returns, consistent with climate-related risk premia (e.g., Huynh and Xia, 2021, 2023). We contribute to this literature by focusing on the bank-lending channel of climate risk. While prior work has largely examined asset prices, we study how banks adjust the quantity and allocation of credit in response to climate-related considerations and how these adjustments propagate to firm-level real and environmental outcomes.

A rapidly growing literature examines how climate risk affects bank lending.[4] Several papers document that banks price climate risk by charging higher interest rates to firms with greater carbon exposure (e.g., Delis et al. 2024; Degryse et al. 2023; Ehlers et al. 2022). Other work shows that firms with higher climate exposure exhibit lower leverage (e.g., Ginglinger and Moreau, 2023; Nguyen and Phan, 2020), while Reghezza et al. (2022) document a decline in lending following the Paris Agreement. More recently, Altavilla et al. (2023) study the role of monetary policy in the transmission of climate risk to bank lending. Green and Vallée (2025) show that explicit coal exit policies reduce lending to coal firms, and Sastry et al. (2026) find limited evidence of lending adjustments following participation in the Net Zero Banking Alliance.

We contribute to this literature along four dimensions. First, we provide evidence on the full chain from bank commitments to firm-level real and environmental outcomes. Despite substantial reductions in credit, investment, leverage, and firm size for high-emission firms, we find no improvement in their realized emissions and only evidence consistent with greenwashing. Specifically, improvements in ESG scores are driven by communication-related components rather than actual environmental performance. To our knowledge, no prior paper documents this full sequence of effects using granular firm-level data. Second, unlike studies that focus on sector-specific policies (e.g., coal exit), we analyze the full cross-section of firms and industries. This allows us to characterize how credit shifts across the entire distribution of emissions, including pronounced nonlinear effects that are not identifiable in single-sector settings. Our results are robust to excluding the most carbon-intensive sectors, indicating that the findings reflect a broad reallocation of credit rather than sector-specific dynamics.

Third, we provide evidence on how the nature and timing of commitments affect their economic impact. We focus on early SBTi commitments, adopted before climate alignment became a widespread

[4] Kacperczyk (2025) provides a broad overview of key mechanisms in the context of banking transition.

institutional norm. In contrast to broader and later initiatives such as the Net Zero Banking Alliance, these early commitments appear to generate economically meaningful changes in lending behavior. This comparison highlights that the effectiveness of voluntary climate commitments depends on their credibility and timing, not merely their existence. Fourth, using loan-level data with firm-time fixed effects, we provide evidence consistent with a supply-side reallocation of credit by banks. Our findings indicate that bank commitments operate primarily through portfolio reallocation rather than through financing the transition of brown firms toward greener technologies.

Overall, our results highlight an important trade-off in climate finance. While bank commitments lead to a reallocation of credit away from high-emission firms, they do not translate into measurable improvements in environmental outcomes, suggesting that voluntary initiatives of this type may have limited effectiveness in facilitating the real transition on their own.

The rest of the paper is organized as follows. In Section 2 we present our data and discuss institutional setting of bank commitments. Section 3 describes our empirical strategy. We present our findings in Section 4 and in Section 5 we briefly conclude.

2. Institutional Framework and Summary Statistics

2.1. Data Sources

Our main analysis covers a sample of international firms over the period 2013-2018. The core dataset combines syndicated lending relationships from Thomson Reuters Dealscan, firm-level GHG emissions from S&P Global Trucost, and firm-level financial information (e.g., investment, size, output, leverage, and volatility) from Compustat Global. We match Compustat Global data to Dealscan following Chava and Roberts (2008) for non-financial companies (NFCs) and Schwert (2018) for lenders. Trucost data are merged using ISIN identifiers. The final sample includes 2,216 firms: 642 headquartered in the United States, 377 in the European Union, 196 in the United Kingdom, and 1,001 in other regions. In additional tests, we supplement the data with firm-level information from Capital IQ (bank versus nonbank financing), Compustat (bank-level controls), Thomson Reuters (institutional ownership), MSCI (ESG ratings), Refinitiv (environmental expenditure, board size, and stakeholder engagement), and Germanwatch (climate risk and policies).

2.2. Institutional Framework of Bank Commitments

In our empirical strategy, we use data on bank commitments under the Science Based Targets initiative (SBTi).[5] For some tests, we also identify NFCs which directly commit to SBTi. The SBTi is a joint initiative by Carbon Disclosure Project (CDP), the UN Global Compact, the World Wide Fund for Nature (WWF) (formerly named the World Wildlife Fund), and the World Resources Institute (WRI), whose purpose is to define and promote net-zero targets in line with the climate science. The overall goal of the initiative is to induce companies to commit to decarbonization pathways to increase the chance that global emissions can be reduced to a level that limits average temperature rise below 1.5°C.[6]

As of early 2026, the SBTi comprises over 10,000 companies with validated targets across 86 countries, collectively representing approximately 41% of global market capitalization.[7] The SBTi commitments vary both in the choice of base year for emissions and the horizon of interim targets. To join the SBTi, a company must first sign a commitment letter stating that it will work to set a science-based emission reduction target. It then has 24 months to develop and submit a target for validation. Once the target has been validated it is disclosed. In practice, banks often do not specify the horizon of their portfolios' greening.

We focus on a sample of 27 banks that joined the SBTi and made public commitments to align with its framework. We describe the sample selection process and list the banks in Table A1 of the Appendix.[8] These committed banks participate in approximately 80% of the loans. Notable names include BBVA, BNP Paribas, Credit Agricole, HSBC, ING, Société Général, and Standard Chartered. In general, banks commit

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[5] Bolton and Kacperczyk (2025) provide more details on the origins of SBTi and the drivers of participation therein.
[6] While SBTi commitments differ in terms of temperature targets (e.g., 1.5°C vs 2°C), the limited availability and comparability of such information during our sample period prevent a clean empirical comparison across commitment types.
[7] See SBTi's January 2026 announcement ("Corporate climate action momentum builds as SBTi reaches 10,000 companies with validated targets") https://sciencebasedtargets.org/news/sbti-celebrates-10000-company-validations.
[8] All firm-level regressions use the full sample of 27 committing banks. As a robustness check, we restrict the sample to the 11 banks with full set of controls; results remain qualitatively similar.

in a staggered fashion. The first wave of commitments occurred in June of 2015 with other important rounds of commitments in November 2015 and April 2016. We label each lender in Dealscan as committed, or not, depending on whether it eventually joins the SBTi, while also keeping track of the bank-specific commitment date.

This institutional setting provides a natural source of variation in banks' climate commitments. Our identification exploits the fact that joining the Science Based Targets initiative constitutes a public commitment by banks to align their activities with the goals of the Paris Agreement. The Agreement increased stakeholder scrutiny and public expectations regarding climate alignment and was often accompanied by changes in internal governance and risk management practices. SBTi has been a work in progress since its inception in 2015. Both the goals and the approaches were gradually defined and refined in a trial-and-error process. The early SBTi guidance primarily focused on firms' operational emissions (Scopes 1-2), and a formal framework for measuring and validating financial institutions' portfolio emissions (Scope 3, financed emissions) was only developed later and finalized in 2022. That said, the decarbonization of the loan book has been on the agenda from the beginning and indeed banks have taken steps in that direction even if these steps were not articulated in black and white in the SBTi guidelines.

Importantly, even before the formal SBTi framework for financial institutions was finalized, several leading banks interpreted their commitments as applying to their lending portfolios. For example, ING, which joined SBTi in June 2015, announced in September 2018 that it would steer its €500 billion lending portfolio toward the Paris Agreement's two-degree goal. Similarly, BBVA, BNP Paribas, and ING signed the Katowice Commitment at COP24 in December 2018, pledging to measure the climate alignment of their lending portfolios. That these public formalizations occurred up to three years after initial SBTi accessions suggests that the underlying shift in lending strategy began at or near the commitment date, consistent with the divergence in lending behavior we observe immediately following accession.

Bank commitments are not random but reflect banks' operating environment and the pressures they face. In practice, these commitments are often associated with stakeholder pressure, which may arise from regulatory conditions, investor expectations, customer relationships, and governance structures. We capture these channels using a set of proxies. To measure climate policy pressure, we use the country-level Climate Risk Index (*CRI*) and a measure of international policy strictness (*International Policy*), under the premise that stricter policy environments increase incentives to commit. To capture ownership-related pressure, we use institutional ownership (*IO*), which proxies for monitoring by institutional investors. To measure client-related reputational concerns, we use a loyalty score (*Loyalty*) that reflects the strength of banks' relationships with their client base. We further include board size (*Board*) as a proxy for governance-related pressure, although its directional effect is ambiguous. In addition, we control for bank characteristics, including the *Tier 1 capital* ratio and bank size (*Lender Assets*). Well-capitalized banks may face less regulatory pressure and have greater financial flexibility, while bank size serves primarily as a control for heterogeneity rather than a theoretically sharp predictor of commitment. Finally, we measure banks' exposure to carbon-intensive lending using *Brown*, defined as the share of bank assets extended to firms with Scope 1 emissions above the 75th percentile of the 2013 distribution. If commitments were primarily driven by risk exposure, one would expect this measure to positively predict commitments. As we show below, this is not the case, which is consistent with a stakeholder-driven interpretation.

We next relate each of the variables to the likelihood of bank commitments. Formally, for each lender in our sample, we define two indicator variables: $Post_{b,t}$ is equal to one if bank *b* has committed by quarter *t*, and zero otherwise; $\text{Committed}_{b,t} = \max_b(\text{Post}_{b,t})$ is equal to one if bank *b* ever commits to SBTi during our sample period. We estimate the following regression model with $Committed_{b,t}$ as the dependent variable, in which we iteratively enter each of the *Pressure* variables, all measured at the annual frequency. In a final specification, we also include all of them jointly.

$$\text{Committed}_{b,t} = a_0 + a_1 \text{ Pressure}_{b,t} + \text{FE} + e_{b,t} \tag{1}$$

Our model includes region and year fixed effects to capture the cross-region and within-year variation in commitments. In the regressions, we cluster standard errors at the bank level. Table 2 reports the results. In the most demanding specification that includes all variables jointly (column 9), we find that *IO* and *Loyalty* are positively related to the likelihood of commitment, while *Tier 1 capital* and *Lender*

Assets are negatively related. The negative coefficients of the two variables suggest that commitment is not primarily driven by the superior financial capacity of banks. The univariate results in columns 1-8 are broadly consistent with the joint specification, with institutional ownership and loyalty emerging as the most robust predictors. Importantly, exposure to brown assets is insignificant in both specifications: banks with higher prior lending to carbon-intensive firms are no more likely to commit than others. While these results are only suggestive, they are consistent with the view that commitments are associated with stakeholder pressure and reputational considerations rather than a direct response to portfolio risk.

An important step in our analysis requires establishing which firms are connected, through prior credit intakes, to banks that are committed to emission reduction targets. For each NFC in our sample, we compile a list of lenders in Dealscan the firm has (ex-ante) borrowed from, over the period 2000-2012. A generic pair of firm f and bank b is defined as connected in quarter t if firm f has ever borrowed from bank b over the period 2000 to 2012, and defined as unconnected, otherwise. A connected firm is labelled as committed if at least one of its lenders is committed at time t. Formally, if B_f denotes the set of connected lenders of firm f, then $Post_{f,t} = max_{Bf}(Post_{b,t})$ takes a value of one from the date of the first commitment of firm f's lenders, and zero before. Committed firms are those whose lenders eventually commit, that is, those for which the indicator variable $Treat_f$ equals one.

2.3. Main Variables and Summary Statistics

We report all summary statistics by type of variation in Table 1. Summary statistics suggest that more than 80% of the NFCs in our sample are connected to committed banks. This large share reflects the fact that committed banks are highly active institutions in the syndicated loan market. To explore additional variation in lending arrangements, we define other variables to capture the strength of such relationships. We first identify lead banks (lead arrangers) in the syndicate along the lines of Ivashina (2009). Such institutions exert a prominent role in the issuance of syndicated loans; for example, they are primarily responsible for loan pricing, typically due to pre-existing stronger relationships with the borrower relative to the other banks in the syndicate. The resulting variable $LeadCommitted_f$ implies that the committed relationship involves at least one such lead bank for the firm; 28% of firms in our sample have a lead-arranger committed to SBTi. We also construct intensive-margin measures capturing the share of committed lenders ($\%Committed_f$) and committed lead arrangers (*%LeadCommitted*). On average, 7.5% and 6% of the total number of lenders involve committed banks and committed lead-banks, respectively. Importantly, in our analysis, we exploit not only the cross-sectional variation due to bank commitment, but also the variation around the timing of bank commitments.

For our analysis of emissions, we access yearly firm-level GHG emissions. We mostly focus on Scope 1 emissions, that is, direct greenhouse gas emissions that occur from sources that are controlled or owned by a non-financial firm. As the first bank commitment happens in mid-2015 and our aim is to rely on ex-ante measures of firm emissions, we start by building a GHG-exposure variable, given by the average firm-level Scope 1 emissions at the start of our sample over the period 2013-14 (that is, before any bank commitment), expressed in tons of emissions and denoted as $S1_f$.

The distribution of emissions is highly skewed. The average firm produces roughly 3.65 million tons of emissions per year with a cross-sectional standard deviation of $S1_f$ equal to 14.96 million tons. In the cross-section of firms, the coefficient of variation with the median is around 38 and the firm in the 75th percentile of the empirical distribution has 28 times higher emissions than the one in the 25th percentile. To deal with such a highly non-linear distribution of Scope 1 emissions, we take the natural logarithm of $S1_{f,pre}$, obtaining a relatively more symmetrically distributed variable, $LogS1_f$. Further, to facilitate a better interpretation of our coefficients, we demean $LogS1_f$; its distribution is summarized in Table 1. Despite the logs, the cross-sectional variation of Scope 1 is still large, e.g. the standard deviation is 2.7.

In some of our empirical tests we also use financial variables. Total debt includes all outstanding short-term and long-term firm debt. The mean value of total debt in our sample corresponds to $1231 million. Again, to mitigate the impact of skewness we take a natural logarithm of the value and define the variable *Total debt* as the log transformation. On average, total debt amounts to roughly 30% of total assets, as is evident from the summary statistics for firm leverage (defined as total debt over total assets). In addition, we gather information on total bank debt, which, on average, equals 40% of total debt; the remaining fraction is predominantly market-financed debt. We also define a variable *Bank debt* as the logarithmic transformation of the raw variable. Throughout our analysis, we apply different firm-level controls, also fixed at their 2013-2014 mean values, including a proxy for firm revenue growth and firm size (log of total assets). Moreover, we proxy for firm-level default risk using a rolling-window stock-return volatility multiplied by firm financial leverage (debt over total assets). Firms exhibit a significant heterogeneity in their risk, with an average risk level of roughly 33.9 pp and an associated standard deviation of 293.2 pp. We also study other financial variables, in particular equity and liquid assets, all precisely defined and summarized in Table 1.

For the analysis of real effects, we define the following variables. Capital expenditure (*CAPEX*) is expressed in log terms and measured at a quarterly frequency. This variable displays a large extent of variation. *ROA* is a firm return on assets. We also use ESG score, which is computed as a weighted average of its three main subcomponents (E+S+G), which, in turn, are obtained as a weighted average of further (sub)subcomponents. These score variables take on values ranging from 0 (worst) to 10 (best). For ESG and *E*-score, the average firm has a score close to 5 points (4.7 for ESG and 5.2 for the E-score), with cross-sectional standard deviations of about 1.2 and 2.2, respectively. For the *E*-score, we additionally gather information on the underlying factors: climate change (resulting from firm performance in terms of, for example, carbon emissions, energy efficiency), natural resources (capturing firm contribution to water stress, biodiversity and land use, and the sourcing of raw material), pollution and waste (proxying for, for example, firms' toxic emissions and waste, product packaging), and environmental opportunities (assessing firms' awareness and ability to exploit future opportunities in clean technologies, energy, and buildings). We also gather information on firm-level annual environmental expenditures. For the small subsample of firms that report them, environmental expenditures amount to approximately 0.4% of total assets at the median.

Finally, to better assess whether the adjustment in credit driven by bank commitments is supply-driven, we study syndicated loan issuance at the firm-bank-year-quarter level. Our analysis considers the extensive, intensive, and combined margins of lending. On the extensive margin, we define an indicator variable equal to one if a bank lends to a firm in a quarter, and equal to zero, otherwise. The set of potential lenders includes all banks involved in prior loan syndicates with the firm, as well as any new lenders in that quarter. The average value of the extensive margin in our sample is roughly 12%. On the intensive margin, we analyze the (log) value of credit extended by each participating lender. We then consider combined specifications in which some lenders provide zero credit while others extend positive loan amounts.

3. Empirical Strategy

Our empirical strategy exploits the fact that, during our sample period (2013-2018), some banks commit to SBTi. We use these commitments in two complementary ways. First, they capture shifts in banks' lending behavior toward high- versus low-emission firms, allowing us to assess whether commitments translate into economically meaningful changes in credit allocation or instead reflect greenwashing. Second, they provide a source of quasi-exogenous variation: firms that had pre-existing relationships (between 2000 and 2012) with committing banks are exposed to these commitments as shocks, enabling us to trace their effects on firm-level outcomes.

Our main specifications study the implications of these bank commitments for different firm-level variables, denoted generically as $y_{f,t}$, such as debt (total debt, bank debt, non-bank debt, leverage), other financial outcomes (e.g., total assets, liquid assets, CAPEX, and ROA), and environmental outcomes (e.g., environmental score, carbon emissions, and environmental spending). Formally, we estimate the following staggered difference-in-differences model:

$$y_{f,t} = \beta_1 LogS1_f + \beta_2 Treat_f + \beta_3 Post_f + \beta_4 LogS1_f{*}Treat_f + \beta_5 LogS1_f{*}Post_t + \beta_6 Post_{f,t} + \beta_7 Post_{f,t}{*}LogS1_f + \theta_1 Controls_f + FE + e_{f,t} \quad (2)$$

In the above equation, $Post_t$ equals one from 2015Q2, the first date in which banks commit to SBTi, onward and zero for any period before. We include this variable to capture common time effects affecting both treated and control firms. Moreover, through the coefficient β_5 we allow for differential time trends across firms with different emission levels (e.g., due to coincident shocks such as the Paris Agreement),[9] thereby generating differential trends in both debt and investment. Finally, the coefficient of interest, β_7, captures the differential effect of bank commitments on firms with higher pre-determined emissions that are connected to committing banks.

Other factors, beyond exposure to climate risk through GHG emissions, may also affect the evolution of debt, investment, and other left-hand side variables. We control for them through a vector of firm-level controls, which includes predetermined revenue growth and log asset size. Both variables are fully interacted with $Treat_f$ and the *Post* indicators. All specifications include firm and time fixed effects, which absorb time-invariant firm heterogeneity and aggregate shocks.[10] In additional specifications, we include industry-time and region-time fixed effects, and in loan-level analyses, firm-time and bank-time fixed effects. We cluster the standard errors, $e_{f,t}$, at the firm level.

Equation (2) represents a model with staggered treatment across firms. Identification requires that, absent bank commitments, connected and unconnected firms with similar pre-determined emissions would have followed parallel trends in their bank debt. In contrast to a standard difference-in-differences model with common time treatment, we face a challenge that in our setting we observe more than a single period in which the treatment effect materializes. The presence of staggered commitments across banks complicates the usual pre-*vs*-post comparisons.[11] Hence, to inspect the parallel-trend assumption, we estimate equation (2) separately for committed and uncommitted firms, which never commit within our sample period, around the first big wave of commitments between Q2 2015 and Q2 2016.

To visualize these dynamics, we estimate an event-study specification with *Bank Debt* as the dependent variable, in which Scope 1 emissions are interacted with time indicators over the period 2013Q4-2016Q2, with 2015Q1 as the omitted category. The regressions include firm and time fixed effects and

[9] For example, this could reflect contemporaneous shocks such as the decline in oil and gas prices around 2015. However, our results are identified from both within- and across-industry variation and remain robust to excluding carbon-intensive sectors such as oil and gas (see Table A6).

[10] In the model with firm and time-fixed effects, the coefficients β_1, β_2, β_3, and β_4 in equation (2) are not identified. Also, note that firm-level emissions are measured before any commitment and are not time varying.

[11] For a formal explanation, see Goodman-Bacon (2021).

controls for predetermined total assets and revenue growth averaged over 2013 and 2014 interacted with the time indicators. We cluster standard errors at the firm level and report 90% confidence intervals. We expect no systematic relationship between emissions and outcomes for unconnected firms, both before and after the commitment date. In contrast, for connected firms, we expect a negative differential effect following 2015Q1, with additional effects around subsequent commitment waves.

4. Results

We first report results related to firm debt, at both firm and loan levels. Next, we show the results for the real corporate decisions, including the investment and leverage choices. Finally, we present the results for environmental outcomes related to firm activities.

4.1. Firm-level Debt: Baseline Results

In our first set of results, we estimate equation (2) with *Total Debt* as the dependent variable. We present results in Table 3 under progressively saturated versions of the model. In column 1, we consider a model with no firm controls or fixed effects. In column 2, we augment the model with firm controls (fully interacted with the post and firm-level treatment indicators). In columns 3 and 4, we add, one at a time, time-fixed effects, which control for changes in firm debt which are common across all firms in our sample, and firm-fixed effects, which account for firm-level time-invariant heterogeneity. Finally, in column 5, we jointly include firm controls, time, and firm-fixed effects.

Across all specifications, the key coefficient of interest, β_7, describing the ex-post relative total debt dynamics for committed firms with above average Scope 1 emissions, is negative (close to -0.024) and statistically significant at conventional levels (e.g., at the 1% level in the most saturated regression model, in column 5). While formal SBTi targets often involve long horizons, lending portfolios can adjust more rapidly through the reallocation of new credit and the non-renewal of existing loans. Consistent with this possibility, we observe significant changes in lending behavior within a few years following commitment.

To assess the economic magnitude of the effects, we take as a reference point the most comprehensive version of the model, in column 5. Following a lender's commitment, firms with a one-standard-deviation higher log-level of Scope 1 emissions experience a relative decline in total debt by 5.5 percent, as compared to other firms without ex-ante lending relationships with committed banks. The economic effect does not depend substantially on whether we include controls or fixed effects. Indeed, the values of the implied effects vary across columns in a tight [5.5, 7.5] percent interval.

In Table 4, we further verify whether the adjustments in total debt are driven by bank debt or non-bank debt. We posit that the relative decline in debt for firms with higher carbon emissions is due to bank commitments. Hence, we should expect greater reductions in bank debt than in non-bank debt. An additional possibility is that banks also affect the financial decisions of other market participants and hence we should also observe adjustments in the level of non-bank debt.

Since we can only dissect bank debt for a subset of the companies in our sample (from Capital IQ), we start by successfully replicating the baseline analysis for total firm debt of such firms in column 1. The results from estimating the regression model over this subsample of firms are qualitatively and quantitatively comparable to those in Table 3 for the larger sample of NFCs. In column 2, we estimate the same version of equation (2) with *Bank Debt* as the dependent variable. Relative to unconnected firms, connected firms experience a reduction in total bank debt if their Scope 1 emissions are relatively larger. From an economic perspective, the decline amounts to 10.4 percent as a result of a one-standard-deviation increase in Scope 1 emissions. In contrast, in column 3, we do not observe any statistically or economically significant adjustment for non-bank debt.

Two features of these results are worth noting. First, the dependent variable in column 2 is total bank debt across all lenders, not only debt from committed banks. The coefficient therefore captures both the direct reduction in lending by committed banks and the extent to which other lenders substitute for this reduction. The fact that total bank debt declines indicates that such substitution is incomplete: affected firms do not fully replace the credit withdrawn by committed banks by borrowing from uncommitted ones. Second, the coefficient for bank debt regressions is estimated on a subsample from Capital IQ and the bank debt variable is left-censored at zero, both of which introduce noise relative to the total debt specification in Table 3. For this reason, while the firm-level decomposition is informative about the channel through which total debt adjusts, the loan-level analysis in Table 6, which compares lending by committed and non-committed banks to the same borrower at the same point in time, provides the cleanest identification of the bank-specific credit supply effect (Khwaja and Mian, 2008). In this regard, the firm- and loan-level results are complementary: the former establishes that affected firms end up with less total bank financing, the latter isolates the supply-side mechanism driving that outcome.

4.2. Firm-level Debt: Robustness and Further Tests

4.2.1. Robustness

In this section, we provide further robustness to our difference-in-differences model. We subject our baseline specification to a series of tests addressing (i) parallel trends, (ii) selection, and (iii) alternative definitions of exposure and emissions.

First, to understand whether the key identification assumption on parallel trends holds, we analyze bank-debt as a dependent variable. We plot the time-varying coefficients in Figure 1. For treated (connected) firms, presented on the left-hand side of the figure, we observe an insignificant effect of Scope 1 emissions on bank debt before the first commitment date (2015Q2) and a negative effect thereafter, which is reassuringly more pronounced also in 2016Q2, that is, the quarter in which the second larger round of commitments takes place. In contrast, for the (unconnected) firms in the control group (right-hand side of the figure), we observe no significant impact of Scope 1 emissions on credit, neither before, nor after 2015Q2. Overall, Figure 1 shows no differential pre-trends across treated and control firms, supporting the validity of our identification strategy.

We caution that our setting does not permit a sharp characterization of the dynamic timing of these effects. The commitments underlying Figure 1 belong to an early wave that is tightly clustered—June 2015, November 2015, and April 2016—and we center the event study on this window, dating Post from 2015Q2. Our broader analysis, by contrast, exploits the full set of staggered bank commitments through 2018. Because commitment timing is staggered across the sample and clustered within this early wave, and because the underlying shift in lending strategy may precede formal accession (anticipation) or follow it with a lag (as the ING and Katowice formalizations discussed in Section 2.2, which arrived up to three years later, illustrate), we cannot attribute the observed change to a single, precisely dated event. At the same time, 2015Q2 is not an arbitrary cutoff: SBTi was launched in May 2015, with the first bank commitments following in June 2015, so no commitment channel could have operated beforehand, and the flat pre-period together with the emergence of the effect at the initiative's launch is consistent with a causal reading rather than a pre-existing divergence between connected and unconnected firms. If anything, the residual timing ambiguity works against detecting a clean break rather than generating one. We therefore interpret our estimates as capturing the effect of the commitment window rather than of any single accession date.

Second, we also test whether our estimates are potentially driven by selection on unobservables. Indeed, as we have argued in the balance table, connected and unconnected firms differ on total assets.[12] As such, differences in asset size may be symptomatic of differences along other dimensions that are not observed. However, this concern is likely irrelevant given that the main coefficient in Table 3 is very similar across specifications as we progressively saturate the model with observable controls and different fixed effects, despite an increase in the regression R-squared by 60 pp moving from column 1 to 5 (following Altonji et al. 2005).[13] We formally verify this statement following the test in Oster (2019). Here, we assume that unobservables correlate with the treatment in the same way as observables (and firm and time-fixed effects) do and fix an upper-bound for the ideal R-squared after controlling for all unobservables to one. Under these assumptions, the upper-bound for our coefficient of interest β_7 is -0.02013, which is strictly less than zero. The coefficient also preserves a similar economic significance.

Third, we also check whether our results hold using different proxies for firms' connections to

[12] Note that in some columns when we control for time-varying firm size in levels and in interactions with commitment, estimated effects are quantitatively similar.

[13] The idea is that, when the controls included in column 5 are omitted from column 1, they are absorbed into the error term. Since the estimated coefficient of $Post_{f,t}$ *Scope 1 changes little between columns 1 and 5, this suggests that the covariance between these controls (firm observables and fixed effects) and our main right-hand-side variable is limited. In turn, this pattern suggests that firm fundamentals (demand-side factors) are unlikely to drive the main results, which is consistent with a credit supply mechanism. Our findings on prices, and especially the loan-level evidence with firm-time fixed effects, further support this interpretation.

committed banks. Our baseline findings, in column 1 of Table A2, are based on the definition of connection using the extensive margin, that is, a firm is connected to any bank that commits through ex-ante loans. In column 2, we substitute this measure with the share of committed banks relative to the number of total lenders a firm is ex-ante indebted to. The main coefficient of interest remains statistically and economically significant. A one-standard-deviation increase in Scope 1 emissions is associated with a reduction in credit by 4.4 percent for firms with one-standard-deviation higher share of committed lenders (17.8%). Next, in column 3, we condition extensive-margin connections on the committed lender being a lead arranger. The coefficient remains negative (though its magnitude decreases by half) and it is statistically insignificant at conventional levels. This lower value of the coefficient may indicate that lead banks have other margins to impose discipline on firms, e.g., via monitoring, or that committed banks cut more lending to brown firms in which they have not been the lead arrangers. Nevertheless, in column 4, when we replace the extensive-margin connection to committed lead arrangers with the share of committed lead arrangers, the results again become statistically significant, though the economic effect is slightly smaller than in column 2 (3.4 percent cut for firms with a one-standard-deviation greater Scope 1 emissions and with a one-standard-deviation higher share of committed lead arrangers). The last two findings suggest that while committed lead arrangers may shield their borrowers from larger credit cuts, being connected to them becomes binding if committed lead arrangers have a sufficient weight in a firm's loan portfolio.

Fourth, we analyze other measures of emissions. In column 1 of Table A3, we present results from our benchmark model using Scope 1 emissions, corresponding to column 5 of Table 3. In columns 2 and 3, we use the levels of Scope 2 and Scope 3, and in column 4, we use Scope 1 intensity. We do not find significant evidence on total debt based on the variation in levels of Scope 2 and Scope 3 emissions. This asymmetry across emission types is consistent with Scope 1 being the most verifiable and directly attributable measure of a firm's carbon footprint. Scope 2 emissions depend on purchased electricity and reflect energy mix choices that are partly outside the firm's direct control, while Scope 3 captures value chain emissions that are notoriously difficult to measure consistently across firms and industries. Banks screening borrowers on carbon exposure would therefore find Scope 1 the most actionable metric, which is also consistent with the greater prevalence of Scope 1 disclosure during our sample period relative to Scope 2 and especially Scope 3. In turn, the results for Scope 1 emission intensity are qualitatively very similar to those based on levels of emissions. This finding is informative because intensity scales emissions by revenue, so the consistency across the two specifications suggests that our baseline result is not mechanically driven by firm size: larger firms do not simply have more debt and higher absolute emissions simultaneously.[14]

Finally, we control for industry-time fixed effects using 4-digit SIC codes as well as region-time fixed effects. We present the results in Table 5, Panel A. Column 1 shows the benchmark result from Table 3, column 2 introduces 4-digit industry-year fixed effects,[15] and column 3 region-time fixed effects.[16] The coefficient of relative treatment becomes somewhat attenuated and statistically insignificant under the 4-digit industry-year specification, which is substantially more demanding and absorbs most within-industry time variation. Importantly, the magnitude remains economically similar to the baseline estimate. This pattern suggests that part of the variation reflects broader reallocations across sectors with different carbon intensity, although the stability of the coefficient across specifications indicates that the result is unlikely to be driven by any single dimension of unobserved heterogeneity. Consistent with this interpretation, columns 3-5 confirm that the baseline effect remains robust when controlling for alternative sources of unobserved heterogeneity.

Overall, the results in this section reinforce the interpretation that our baseline estimates reflect a credit supply response rather than confounding firm-level dynamics.

4.2.2. Economic Mechanism

Having established the robustness of the baseline result, we now turn to understanding the economic

[14] Tables A4 and A5 show that results are qualitatively similar when using emission levels or intensity measures.
[15] Industry-time fixed effects also absorb time-varying sectoral shocks, including those affecting carbon-intensive industries such as oil and gas. Results are robust to excluding these sectors (Table A6).
[16] Regions broadly correspond to continents. Limited within-country variation in the firm-level sample prevents the inclusion of more granular location-time fixed effects; this is addressed in the loan-level analysis using firm-time fixed effects.

mechanism driving the lending response. We consider the following two hypotheses. First, risk-averse banks cut credit to high-emission firms and channel credit to low-emission firms if they recognize that financial risk associated with their operations positively correlates with their emission activity. An alternative hypothesis is that committing banks make their credit decisions strictly based on their non-risk considerations, such as reputational concerns or stakeholder pressure. To distinguish between the two hypotheses, we conduct three tests: (i) we directly control for business risk, also interacted with commitments; (ii) we analyze loan maturity (financial risk stemming from physical risk and policy transition risk due to climate change is more important for the long- and medium-term); (iii) we analyze loan-level data and control for firm-time effects, which controls for all unobservable time-varying firm fundamentals, including any unobserved firm-level risk.

A relevant question is whether the described adjustments conditional on firm-level Scope 1 emissions are driven by committed banks' preferences for decarbonization, which could be intrinsic or driven by reputational risk or stakeholder pressure, or the banks' being more responsive to differences in carbon transition risk among firms with different levels of emissions.[17] In the context of lending, the primary source of the latter, firm-level risk of concern to lenders would be default risk due to stranded assets or costly transition. To distinguish between the two forces, in column 4 of Table 5, Panel A, we analyze the impact of Scope 1 emissions on total debt controlling for a proxy of firm-level default risk, defined as a (lagged) product of stock returns volatility and firm leverage. Our results indicate that relatively riskier firms connected to committed banks indeed experience a relative decline in their total debt (by 5.7 percent in response to an interquartile increase in default risk), as compared to unconnected firms. Quantitatively, after controlling for the risk channel, committed firms with a one-standard-deviation higher Scope 1 emissions experience a credit cut of 3.8 percent (relative to uncommitted firms), whereas the overall effect without controlling for firm risk is 5.5 percent.

[17] Apart from the differential response of banks to credit risk, all banks could ration their credit based on enhanced risk irrespective of their commitment status. This effect is absorbed by the level effect of *Risk* variable.

To shed more light on the bank motives, we examine whether SBTi participants apply mechanical (industry-based) rules and cut off firms in proportion to their emission levels, or they condition on whether such firms are trying to improve or not. Our proxy for improvement is a relative ranking of firms in terms of their emission intensity within their industries. To test this hypothesis, we sort companies within their own two-digit SIC industry according to their 2013-2014 emission intensity levels and form the relative rank of each company from lowest intensity to highest (*Intensity Rank*). We further demean the variable within each industry and interact it with our baseline model. We estimate a similar regression model to the one in column 4 and report the results in column 5. We find no statistically significant evidence that differences in within-industry intensity matter for bank debt. Importantly, controlling for the intensity rank does not alter significantly our baseline estimation results.

A possible limitation of the above test is that it largely looks at past emission numbers as proxies for future decarbonization whereas banks may be truly forward looking and condition on future actions of corporate emitters. To examine this issue more directly, we analyze whether banks differentiate between high-emission firms that make explicit commitments to reduce emissions and those that do not. Specifically, we interact firm emissions with indicators of firm-level climate commitments. We report the results in Table A7. The estimated effect of bank commitments on borrowing remains negative for high-emission firms regardless of whether they announce their own transition commitments. The triple interaction captures differences in the intensity of the response across firms but does not alter the main finding that bank commitments are associated with reduced borrowing by carbon-intensive firms. While the triple interaction is statistically significant for total debt and leverage, similar interactions are not statistically significant for other financial or real outcomes. This pattern indicates that borrower commitments do not systematically alter the effect of bank commitments on firms' financing outcomes. The results do not suggest that borrower commitments systematically drive the lending response. This indicates that the reduction in borrowing among high-emission firms following bank commitments is not driven by firms' own climate pledges.

In Table 5, Panel B, we additionally study changes in debt maturity. This margin provides a useful way to distinguish between risk-based and non-risk-based explanations. If banks adjust lending in response to climate risk, one should expect a shortening of loan maturities, as such risks, both physical and transition, are primarily medium- to long-term in nature. In contrast, if lending adjustments reflect a reallocation of credit not driven by borrower risk, we should expect no systematic change in maturity. To this end, in columns 1 to 4 we analyze log maturity, while columns 5 to 8 focus on the likelihood of short-term loans (below the median). We find no significant change in maturity choices, consistent with a supply-side reallocation that is not explained by borrower risk.

These findings are consistent with banks reallocating credit in response to non-risk considerations, such as reputational concerns, stakeholder pressure, or internal climate mandates, rather than adjustments driven by borrower fundamentals. Two caveats on interpretation are warranted. First, although our loan-level specifications absorb firm-by-time fixed effects—differencing out, within the same firm and quarter, the lending of committed versus non-committed banks and thereby any firm-level exposure to contemporaneous climate regulation or to stranded-asset risk—we cannot fully rule out that committed banks differ from non-committed banks in unobserved ways correlated with borrowers' transition risk. Committed lenders may, for instance, be more attuned to the risk that carbon-intensive assets become stranded under future climate regulation, in which case part of the reallocation we document would reflect differential risk assessment rather than commitment per se. Second, our firm-level risk proxy—the product of return volatility and leverage—is backward-looking and may not fully capture forward-looking stranded-asset risk; the maturity results (Table 5, Panel B) and the evidence that prior brown-asset exposure does not predict commitment (Table 2) mitigate, but do not eliminate, this concern. We therefore interpret the evidence as consistent with a commitment-driven, supply-side reallocation of credit, while acknowledging that a residual role for differential risk assessment cannot be definitively excluded.

4.3. Loan-level Estimates

In this section, we present results based on the loan-level sample. Table 6 examines the interaction between the Post and Commitment indicators and firm Scope 1 emissions along both the extensive and intensive margins of lending. Our dependent variable in columns 1 to 4 is the log of credit volume plus one if a lender provides a loan to the firm, while column 5 uses the log of credit volume conditional on lending. Column 6 isolates the extensive margin using an indicator equal to one if a firm receives a loan. If a lender has previously participated in a loan to the firm but does not in the current period, lending is coded as zero in columns 1 to 4 and 6. Accordingly, columns 1 to 4 combine the intensive and extensive margins. Firm controls include ex ante log total assets and revenue growth, interacted with Post, Treat, and their interaction. Bank controls include ex ante log assets and the Tier 1 capital ratio averaged across banks. In all specifications, we include firm-year-quarter fixed effects, which absorb time-varying firm-level shocks, including credit demand. This specification allows us to compare lending decisions of committed and non-committed banks to the same firm at the same point in time, providing a direct test of whether the observed credit adjustment reflects shifts in credit supply.[18]

We find that the adjustment happens mostly along the extensive margin. Compared to other banks, committed banks reduce their participation in loans to firms with higher Scope 1 emissions. At the same time, we do not find a significant result on the intensive margin, that is, committed banks extend their syndicated loans as an in-or-out decision and do not partially cut the quantity of credit within a loan that they participate in. The results that combine intensive and extensive margins are again statistically significant. This pattern is consistent with a shift in credit away from high-emission firms operating through discrete lending decisions rather than marginal adjustments in loan size.

The estimated coefficients for the combined intensive and extensive margins (column 4) imply that a one-standard-deviation increase in carbon emissions results in a reduction of 8.3 % in combined loan margins by committed banks. For the extensive margin alone (column 6), a one-standard-deviation increase in Scope 1 emissions results in a reduction of the probability of loan participation by 12% of the mean and 4% of the standard deviation. These results are robust. In Table 6, in addition to firm-time fixed effects, we alternately control for bank observables, bank fixed effects, or firm-level controls interacted with bank commitments. In Appendix Table A8, we control for bank-time fixed effects or for loan variables such as

[18] The increase in the coefficient magnitude with additional controls also implies a significant lower bound under the Oster (2019) test.

bank as prior lead arranger or relationship length. Finally, we also use OLS with log values or use a Poisson model. Across all specifications, the results remain qualitatively and quantitatively similar.

In the regression with bank-year-quarter fixed effects, the estimated coefficient is very similar to the regression without these fixed effects. Since we control exhaustively for bank time-varying observed and unobserved variation, including total bank lending, this result is consistent with a shift in lending away from high-emission firms toward lower-emission firms. That is, controlling for overall bank-level lending, we find that committed banks cut (increase) credit to the same firm at the same time depending on whether the firm has high or low emissions.

In our loan-level analysis, we explicitly require that a committing bank have a full set of controls to enter our loan-level regression, which as we argued restricts our sample to 11 banks only. To assess the sensitivity of our results to this selection rule, we repeat our loan-level analysis on a full set of 27 committing banks with bank and firm-time fixed effects but no bank controls. Our results, in Table A9, are qualitatively similar to those estimated on the restricted sample, thus reinforcing our baseline results.

We also look at loan prices as another margin through which credit supply could operate. In the absence of detailed data on loan prices, our dependent variable is total interest expenses on debt relative to total debt. We present our results in Table 7. While we detect some increase in borrowing costs, the magnitude is economically small relative to the contraction in quantities, indicating that adjustment primarily occurs along the quantity margin. A one-standard-deviation increase in Scope 1 emissions implies an increase in debt interest expenses by 2% of the mean or 3% of the standard deviation of expenses. This result is not entirely surprising given that banks commit to greening out their loan portfolios, which is consistent with committing banks focusing on reducing exposure to high-emission borrowers rather than adjusting prices while maintaining lending relationships.

Overall, the loan-level evidence indicates that committed banks reduce credit supply to high-emission firms and shift lending toward greener firms. These adjustments are not fully offset by alternative sources of financing, consistent with the firm-level contraction in credit documented above.

4.4. Real Effects: Deleveraging and Investment

In our results so far, we observe significant heterogeneous changes in firm-level financing capacity due to bank commitments. The key question is whether these changes translate into broader financial and real adjustments for affected firms. Our empirical tests are guided by the theoretical literature on corporate finance decisions of firms facing shocks to real and financial flexibility. In particular, the model of Bolton et al. (2019) in which firms face costly access to external financing predicts the following outcomes: (1) firms should reduce their reliance on external finance and their leverage should go down; (2) firms should reduce their investments; (3) firms should build up liquid asset reserves for precautionary reasons.

We begin by investigating empirical effects on firm deleveraging. We report the results in Table 8. For ease of comparison, across all measures, we restrict our sample to the same set of companies. In columns 1 and 2, we conduct our analysis using *Bank Debt* and *Total Debt* as dependent variables. The results are similar to those in the unconstrained sample. In column 3, we use firm leverage as a dependent variable, defined as total debt over total assets. We find that committed firms with relatively higher Scope 1 emissions experience a decrease in leverage, but the magnitude of the adjustment is quite small and statistically weak and economically small. A one-standard-deviation increase in Scope 1 emissions implies a relative reduction in leverage for connected firms (as compared to unconnected ones) by just 30 basis points. This effect is small when compared to both the unconditional mean leverage in the sample (equal to 30%) and to the decrease in the numerator, that is, total debt, associated with the same variation in Scope 1 emissions (5.5 percent).

This result motivates our investigation of total assets as a separate dependent variable. We find that bank commitments are associated with a significant reduction in total assets for companies with high levels of Scope 1 carbon emissions. Connected firms with a one-standard-deviation higher Scope 1 emissions reduce the overall size of their balance sheets by roughly 2 percent. When we separate out the equity portion of firm assets, in column 5, we do not observe any significant variation in firm equity associated with bank commitments. This result implies that firms do not substitute debt finance with equity funding, consistent with equity finance being relatively more costly (Bolton and Kacperczyk 2021, 2023). Instead, our findings show that bank commitments are associated with deleveraging by firms with relatively higher carbon emissions.

Another dimension of firm behavior we consider is firm investment, measured by *CAPEX*. Our results, in column 6, show a significant cut in firm investments. Connected firms with a one-standard-deviation higher Scope 1 emissions reduce their *CAPEX* by 4 percent (as compared to unconnected NFCs). Overall, while the investment result is consistent with the deleveraging effect in that lower asset base requires less investment, it may also reflect that tighter credit conditions limit the ability of high-emission firms to finance investment, including investments in green technologies.

Next, we study the effect of financing constraints on the accumulation of internal liquid assets, along the lines of the cash hoarding hypothesis. We define liquid assets as the ratio of cash plus short-term investments and total assets, *LIQAT*. We report results in column 7 using *LIQAT* as the dependent variable. We find a positive, albeit statistically insignificant, effect of bank commitments on liquid assets.

As a final and auxiliary prediction to the model of financing decisions, we explore the effect of bank commitments on firm profitability, measured using the return on assets (*ROA*). We report the results in column 8. We find that following bank commitments, affected firms with high emissions subsequently realize statistically higher ROAs. This pattern is consistent with a selection effect whereby firms, facing tighter credit constraints, abandon lower-return projects, thereby increasing the average profitability of remaining investments.

These real adjustments raise a natural follow-up question: whether tighter credit constraints translate into improvements in firms' environmental performance.

4.5. Environmental Performance: Emissions, ESG Metrics, and Expenditures

The underlying premise of bank commitments is their disciplinary effect on emission production. A simple mechanism is that banks either cut lending to high-emission firms, inducing them to scale down, or continue to lend in a way that facilitates investment in cleaner assets. Both channels may be reinforced by bank monitoring. Our results so far suggest that the dominant channel appears to be credit reduction. In this section, we examine whether the assets of high-emission companies indeed become greener as a result.

To evaluate this mechanism, we consider a host of regression models in which the dependent variables measure different dimensions of firms' environmental performance. We present the first set of findings from this analysis in Table 9. To begin with, we examine whether connected firms reduce their future Scope 1 emissions. Our dependent variable is one-year-ahead Scope 1 emissions measured on an annual basis. While the results, in column 1, suggest that the average connected firm reduces its Scope 1 emissions by a significant 29 percent (exponentiated), we do not find any additional marginal effect for firms with relatively higher Scope 1 emissions, which is the key margin. Since adjustment of environmental performance may be a slow process, we also study whether affected firms change their emissions significantly over the longer horizon of up to 3 years (see columns 2 to 5). Again, we do not find statistically significant evidence that emissions change over the longer horizon. Finally, we test whether such firms express formal commitments to future emission reduction, using SBTi commitments as a relevant proxy (column 6). Again, the effect is statistically insignificant. In sum, despite firm-level real and financial effects associated with bank commitments for high-emission firms, we do not find any reduction in carbon emissions, which represent realized environmental outcomes.

Next, we enhance our analysis with a broader set of sustainability-related measures. Our first measure is MSCI ESG score. The results, in column 7, show no statistically significant treatment effect; that is, connected firms with higher emissions do not seem to improve their ESG metrics. However, when we zero in on the *E* component of the score, which tracks environmental performance at the firm level, in column 8, we find statistically significant differences. Connected firms with a one-standard-deviation higher Scope 1 emissions improve their *E*-scores by roughly 14 basis points (as compared to firms with similar levels of emissions but without connections to committed banks), about 6% of the cross-sectional standard deviation. In contrast, we do not observe any significant adjustment in environmental expenditures, neither when they are measured in logs (column 9), nor when they are scaled by total assets (column 10). However, this variable is available for only a small subset of firms and should be interpreted with caution. In column 11, we further study whether affected firms increase their usage of renewable energy. We find no significant result.

As a final step in our analysis, we investigate more granular drivers of the improvement in the *E*-factor of ESG. The results are presented in Table 10. For ease of interpretation, we begin by reporting, in columns 1-4, the results related to the overall ESG score and to the E (environmental score), S (social score), and G (governance score), respectively. Only the *E*-score displays a significant improvement for affected firms. In the subsequent tests, we use different subcomponents of the *E*-score as our left-hand-side variable. We find only a marginally significant improvement (at the 10% level) in climate change mitigation efforts (column 5), and no changes in waste reduction through a revision of product packaging policies (column 7) or carbon emissions (column 9). If anything, firms perform worse in terms of their usage of natural resources (column 6). The only improvement observed in the *E*-score, in column 8, results from an improvement in the awareness of affected firms about environmental future opportunities, such as those related to clean technology.

Given that after bank commitments, firms previously borrowing from these banks have lower total assets but their carbon emissions do not change, one possible interpretation is that affected firms may be divesting relatively greener assets rather than reducing carbon-intensive operations. At the same time, some adjustments may not be captured in near-term Scope 1 emissions. For example, firms may reduce medium-term emissions through investments in intangible green assets such as R&D, which are not captured by CAPEX. It may also take years for a brown firm to meaningfully reduce its carbon footprint. Nonetheless, we find no significant difference in SBTi NFC commitments to future emission reductions depending on whether firms previously borrowed from committed banks, suggesting that affected firms do not even signal an intention to decarbonize. The results in Table A10 confirm that this conclusion extends to the full set of environmental outcomes examined in Tables 9 and 10. The interaction of firm and lender commitments does not produce significant improvements in ESG scores, environmental expenditures, or renewable use, reinforcing the interpretation that borrower pledges do not materially alter the environmental response documented in our baseline analysis.

The results in Table A7 sharpen this interpretation further. Committed banks cut credit most aggressively to brown firms that have themselves announced emission reduction pledges, rather than rewarding such pledges with easier access to financing. This pattern is consistent with bank skepticism toward firm-level climate commitments. Banks appear not to treat these pledges as credible, consistent with the absence of emission reductions in our data. Taken together, the evidence in this section points to a coherent pattern consistent with greenwashing: affected firms improve their environmental communication, as captured by the environmental opportunities' subcomponent of the *E*-score, without changing their actual environmental performance, and committed banks respond by cutting credit rather than rewarding these pledges. The improvement in ESG scores is primarily driven by communication rather than action, and the banks themselves do not find it credible.[19] These findings suggest that credit contraction alone is insufficient to induce environmental transition.

4.6 Nonlinearities in Carbon Emissions

Our results so far evaluate the role of commitments and firm emissions for the average firm in our sample. Given that bank commitments target carbon-intensive exposures, one would expect the effects to be concentrated among the highest-emission firms. We therefore examine whether the real effects vary across the distribution of emissions. Formally, we split firms into quintiles using the distribution of ex-ante Scope 1 emissions and estimate the triple difference regression model with interactions representing each of the five quintiles. We consider the following five variables as our dependent variables: *Total Debt*, *Bank Debt*, *Nonbank Debt*, *CAPEX*, and *LogS1*.

We report the results from the regression models in Table 11. We find strong nonlinearities across the emissions distribution: relative to firms in the highest-emission quintile, firms in the lowest-emission quintile experience a 15% increase in total debt, compared to firms in the highest-emission quintile. The results, in columns 2 and 3, further indicate that this effect can be entirely explained by the adjustment in

[19] We do not find any significant effects related to firms' commitments to future emissions reductions. The results are reported in the Appendix, Table A10.

bank debt (though there is a significant effect for quintile 2 for nonbank debt). The effect for bank debt is particularly striking as the difference between highest and lowest-emission quintiles is an economically large 44%. Effects are mild for the remaining firms.

Consistent with the debt results, we find that firms in the lowest-emission quintile increase CAPEX by 17% relative to higher-emission firms. Importantly, despite these strong nonlinear financial and real effects, we find no corresponding reduction in carbon emissions even though the average effect of $Post_{f,t}$ is negative consistent with the firms reducing their emissions.

4.7. The Effects on Bank Operations

We next examine how bank commitments affect bank-level outcomes. This analysis provides insight into whether commitments translate into measurable changes in portfolio composition and whether they entail economic costs for banks.

In our analysis, we conduct two types of tests. First, we study the impact of bank commitments on the decarbonization of the bank portfolio that is exposed to syndicated loans. Do we observe that banks that commit reduce the carbon footprint of their portfolios? We test whether bank commitments lead to a reduction in the carbon intensity of banks' lending portfolios. We answer this question using four different metrics of bank portfolio carbon metrics as dependent variables. First, we look at the average value of Scope 1 emissions of assets per number of loans (*S1/#Loans*). Next, we relate the bank portfolio's carbon footprint to the loan volume (*S1/Loan Volume*). Third, we look at the imputed loan weighted Scope 1 emissions, expressed in logs (*WLogscope1*). Finally, we use the same measure based on emission intensity (*Wscope1int*). The main independent variable is $Committed_{b,t}$. We estimate the model using weighted-least square regression. The weights in the regression are based on the number of loans granted by each bank in a given year. We present the results of the analysis in Table 12.

Our results indicate that bank portfolios become significantly less carbon-intensive following commitment. The subsequent change in carbon footprint is negative for three out of four measures, and it is statistically significant for *S1/Loan Volume* and *Wscope1int*. We note that the results do not reflect the entire carbon footprint of the bank assets since we only have data on syndicated loans and even within these data we do not have for all the loans the loan volume for each bank in each loan.

Second, we examine the impact of bank commitments on their profits, measured by their ROA. This test allows us to establish whether the commitments are profit increasing (because of reputational benefits, lower cost deposits, or lower regulatory burden), or profit destroying even if they respond to managerial taste for green investment. We report the results from this test in column 5. We find no statistically significant effect on bank profitability. This suggests that the portfolio adjustments associated with commitments do not impose large net costs on banks, potentially reflecting offsetting pecuniary and non-pecuniary effects.

Taken together with our firm-level results, these findings indicate that while bank commitments lead to measurable changes in portfolio composition, these adjustments operate primarily through credit reallocation rather than inducing environmental improvements at the borrower level.

5. Conclusions

One of the central questions in the debate on climate policy is whether the financial sector can discipline firms to improve their environmental performance and whether such pressure translates into meaningful emissions reductions. We examine this question in the context of global syndicated lending between 2013 and 2018, exploiting bank-level climate commitments as shocks to lending relationships identified through firms' prior credit exposures. We find that firms with higher Scope 1 emissions that have established relationships with committed banks receive less bank credit following these commitments. The effects are driven by bank lending behavior and are absent prior to commitment, consistent with a supply-side reallocation of credit away from high-emission firms that is not explained by borrower risk.

This reallocation has real consequences. Affected firms reduce total debt, leverage, assets, and investment, with stronger contractions among the most carbon-intensive firms. However, despite these financial and real adjustments, we find no evidence of improvements in environmental performance. Firms do not reduce emissions or increase adoption of formal climate commitments. Instead, the evidence is consistent with greenwashing, suggesting that reduced access to bank credit does not induce meaningful decarbonization.

Taken together, our findings indicate that banks influence the allocation of capital across firms but do not facilitate the transition of high-emission firms toward lower carbon intensity. Rather than financing decarbonization, climate commitments by banks lead to a reallocation of credit away from carbon-intensive firms without achieving corresponding environmental gains.

Our results also speak to the design and effectiveness of climate-related financial initiatives. We focus on early commitments adopted before climate alignment became a widespread institutional norm and show that these commitments generate economically meaningful changes in lending behavior, consistent with binding constraints at the bank level. However, as climate commitments scale and become more diffuse, their equilibrium effects may change. In particular, broader and later initiatives may be less effective in generating differential lending behavior, either because commitments become less binding or because widespread adoption compresses cross-bank variation in lending standards.[20] These patterns suggest that the effectiveness of voluntary climate commitments depends not only on their adoption but also on their credibility, timing, and the extent to which they generate cross-sectional variation in constraints. When commitments are early and selective, they can induce meaningful changes in financial behavior. As they become widespread or lose enforceability, their ability to generate differential lending behavior, and thus to discipline firms through capital allocation, may weaken.

More broadly, our findings raise questions about the role of financial institutions in the transition to a low-carbon economy. While banks can shift the allocation of capital away from carbon-intensive firms, our evidence indicates that such reallocation alone is insufficient to induce emissions reductions. Importantly, this does not imply that the influence of the banking sector is limited. On the contrary, our results show that banks exert meaningful discipline through credit supply, even as specific institutional

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[20] The most notable example of such event is the emergence and subsequent demise of Net-Zero Banking Alliance, which at the peak of its activity in 2024 involved 140 banks. On October 3, 2025, the 120 remaining members voted to stop work immediately, transitioning the organization from a membership-based alliance to a guidance framework.

arrangements evolve or weaken. Rather, the key limitation is that this influence operates primarily through capital reallocation rather than through facilitating technological transition. This highlights the limits of relying on financial sector discipline as a primary mechanism for corporate decarbonization and underscores the importance of complementary policies that directly incentivize firms to adopt cleaner technologies.

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Figure 1. Bank Debt: Parallel Trends

This figure plots the coefficients from the time-varying version of the baseline bank debt regression where bank debt is the dependent variable, and the variable of interest is Scope 1 emissions interacted with dummies for each time period. 2015Q1 is the omitted base level and is one period before any bank commits to reducing emissions, indicated by the dashed red line. The left panel shows the results for firms that had borrowed from at least one bank that commits and the right panel shows the results for firms that had never borrowed from a bank that commits until period *t*. The regressions include firm and time fixed effects and controls for predetermined total assets and revenue growth averaged over 2013 and 2014 interacted with the date indicators. Standard errors are clustered at the firm level and confidence intervals are 90%.

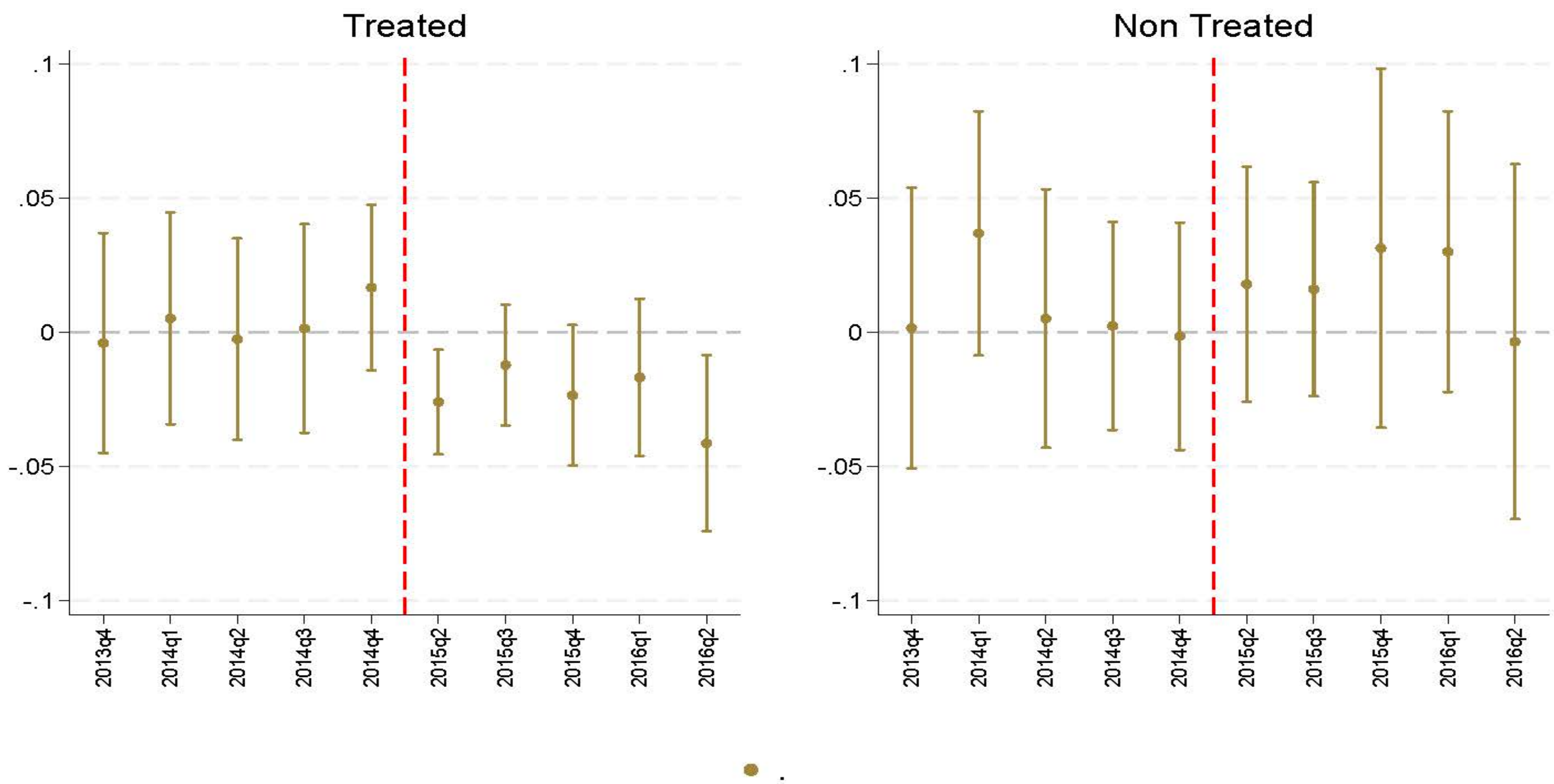

Table 1: Summary Statistics

The sample period is 2013-2018. Ex ante variables are averaged over 2013-14. The distributions of Log_S1 and bank-level variables are summarized using annual frequency of the data. The rest of the data are sampled quarterly.

VARIABLES		(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Bank-Level Variables	**Description**						
CRI	Climate risk indicator (aggregate)	592	0.4493	0.2887	0.1833	0.4050	0.6433
IO	Bank-level institutional ownership	615	0.1516	0.1430	0.0419	0.1094	0.2245
Loyalty (Ref: Ec_Re_CL_D01_s)	Bank-level score of client loyalty towards the bank	776	0.5828	0.2972	0.1790	0.6712	0.8094
Board	Log(Board Size)	776	0.5229	0.2895	0.2503	0.6472	0.7710
International policy	Strength of international climate policy (country-level)	514	0.5494	0.2147	0.4200	0.5900	0.6800
Tier 1 capital	Bank tier 1 capital ratio	1172	13.0215	3.5940	10.7000	12.4500	14.7600
Lender Assets	Log(Bank Assets)	1172	10.7883	1.2792	9.9677	11.0945	11.9575
Brown	Loan portfolio exposure to brown assets (>75th pctl. of emissions)	1090	0.4395	0.2821	0.2560	0.3977	0.6250
Firm-Level Variables							
Log-S1$_{ft}$	Log (Scope-1 Emissions tonnes)	10,385	11.94	2.67	10.16	11.66	13.52
Log-S1$_{f}$ (ex-ante)	Log-S1 (ex-ante)	2216	11.79	2.67	10.02	11.51	13.35
Log-S1$_{f}$	Log-S1 (ex-ante, demeaned)	2216	0	2.67	-1.77	-0.28	1.56
Treat$_{f}$	Firm indicator if a firm ever has a lender that commits	43,489	0.8136	0.3894	1	1	1
Post$_{f,t}$	Time indicator after a firm has at least 1 prior lender committing	43,489	0.4016	0.4902	0	0	1
% Committed$_{f}$	% of a firm's prior lenders who eventually commit	43,489	0.0746	0.1230	0	0	0.1311
Lead Committed$_{f}$	Firm indicator if a firm ever has a prior lead lender that commits	43,489	0.2844	0.4512	0	0	1
% Lead Committed$_{f}$	% of a firm's prior lead lenders who eventually commit	43,489	0.0587	0.1199	0	0	0.0909
Total Debt	Log(Total Debt)	43,489	7.117	1.559	6.183	7.342	8.362
Bank Debt	Log(Bank Debt +1)	34,371	5.367	2.452	4.564	6.019	7.226
Non-Bank Debt	Log(Non-Bank Debt +1)	34,371	5.471	2.881	3.943	6.439	7.788
Leverage	Total Debt / Total Assets	43,489	0.304	0.156	0.200	0.305	0.375
Assets	Log(Total Assets)	43,489	8.503	1.186	7.707	8.600	9.558
LIQAT	Liquid Assets/Assets	43,467	0.095	0.086	0.038	0.083	0.117
Equity	Log(Total Equity)	42,312	7.449	1.167	6.721	7.579	8.477
ROA	Return on Assets	40,294	0.009	0.025	0.003	0.010	0.018
Risk	Leverage * Prior 12 month equity volatility	39,614	33.872	293.210	5.157	7.806	12.199
Revenue growth (ex-ante)	% growth in revenue	2216	0.0542	0.2351	-0.0492	0.0198	0.0902

Assets (ex-ante)	Log(Total Assets)	2216	8.36	1.22	7.56	8.44	9.40
Capital Expenditures	Log(Capital Expenditure)	39,987	3.696	1.559	2.730	3.900	5.124
Interest Expense	Interest Expense / Total Debt, winsorized 2.5% both tails	38,850	0.012	0.008	0.008	0.011	0.014
ESG Score	MSCI Environmental Social and Governance score	32,874	4.732	1.164	4	4.7	5.5
Env Score	MSCI Environmental sub-score	32,874	5.150	2.210	3.5	4.9	6.5
Soc Score	MSCI Social sub-score	32,874	4.489	1.760	3.4	4.5	5.6
Gov Score	MSCI Governance sub-score	32,872	5.594	2.084	4.1	5.5	7
Climate Score	MSCI Climate Change sub-sub-score	30,361	6.410	2.872	4.4	6.7	9
Natural Resource Score	MSCI Natural Resource sub-sub-score	25,477	4.979	2.480	3.3	4.7	6.5
Waste Mgmt Score	MSCI Waste Management sub-sub-score	24,877	5.481	2.575	3.6	5.4	7.5
Env Opp Score	MSCI Environmental Opportunity sub-sub-score	13,849	4.563	1.559	3.4	4.4	5.7
Carbon Score	MSCI Carbon sub-sub-score	27,586	6.920	2.697	5.3	7.2	9.5
Env Exp_{t+1}	Next year Log(Environmental Expenditures + 1)	10,466	4.506	3.130	2.092	3.967	6.456
Renewable Use	Indicator if a firm uses renewables	36,489	0.506	0.500	0	1	1
Firm Commitments	Time indicator if a firm commits	43,489	0.009	0.094	0	0	0
Maturity	Log(Maturity)	945	3.726	0.716	3.584	4.064	4.094
Loan-Level Variables							
Extensive + Intensive	Log(Loan Amount +1)	60,907	0.465	1.375	0	0	0
Extensive	Indicator if lender makes a loan to a firm in a quarter	60,907	0.118	0.322	0	0	0
Intensive	Log(Loan Amount + 1)	7170	3.951	1.512	3.266	4.070	4.823
$ Extensive + Intensive	Loan Amount (USD millions)	60,907	10.853	43.642	0	0	0
$\mathrm{Post}_{b,t}$	Time indicator after a lender commits	60,907	0.032	0.176	0	0	0
Treat_{b}	Lender indicator if a lender ever commits	60,907	0.110	0.313	0	0	0
Bank Assets (ex ante)	Log(Total Assets)	7167	11.79	0.36	11.81	11.93	11.96
Bank Tier 1 (ex ante)	Bank tier 1 capital ratio	7063	12.49	1.15	12.18	12.68	13.14
Bank Prior Leader	Indicator if the lender was a prior lead lender to the firm	60,907	0.33	0.47	0	0	1
Relation Length (quarters)	Time since first loan in a firm-lender pair	60,907	46.79	25.25	27	48	66

Table 2: Predicting Bank Commitments

The sample period is 2015-2018. The dependent variable is $Committed_{b,t}$. *CRI* is the country-level measure of climate risk. *IO* is the percentage level of bank ownership that is held by institutional investors. *Loyalty* measures the loyalty of the bank clients. *Board* is the natural logarithm of the number of board members sitting on a bank's board. *International policy* measures country-level strength of international climate policy. *Tier 1 capital* is bank tier 1 capital ratio. *Lender Assets* is the natural logarithm of bank assets. *Brown* is loan portfolio exposure to brown assets (75th percentile and above of emissions). All regressions include year and region fixed effects. Standard errors are clustered at the bank level. ***p<.01, **p<.05, *p<.1.

DEP. VAR.: $Committed_{b,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CRI	0.0467								0.1556
	(0.0576)								(0.1210)
IO		0.2749**							0.3509*
		(0.1221)							(0.1972)
Loyalty			0.3931*						0.3726**
			(0.2084)						(0.1832)
Board				0.0284					-0.0271
				(0.0588)					(0.0925)
International policy					-0.0128				0.1489
					(0.1877)				(0.2399)
Tier 1 capital						-0.0020			-0.0182*
						(0.0046)			(0.0098)
Lender Assets							0.0037		-0.0696*
							(0.0046)		(0.0400)
Brown								-0.0068	-0.0242
								(0.0526)	(0.0798)
Observations	591	614	358	358	513	614	614	578	278
R-squared	0.217	0.244	0.275	0.249	0.216	0.216	0.216	0.212	0.306
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: The Effects of Bank Commitment on Total Firm Debt

The dependent variable is *Total Debt* of firm *i* at year-quarter *t*. A firm is defined as having a committed lender if at least one lender with whom they have a prior credit relationship has committed to reducing emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All variables are defined in Table 1. Columns (1)-(5) progressively add controls and more stringent fixed effects. The sample period is 2013-2018. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Total Debt		
$Post_{f,t}$* Log-$S1_f$	-0.0284*	-0.0257**	-0.0249**	-0.0216***	-0.0205***
	(0.0155)	(0.0121)	(0.0121)	(0.0075)	(0.0075)
$Post_{f,t}$	0.3764***	-0.1023	-0.1338	0.1906	0.1299
	(0.0366)	(0.2611)	(0.2618)	(0.2062)	(0.2071)
$Post_t$ * Log-$S1_f$	-0.0234**	-0.0057	-0.0064	-0.0074	-0.0087
	(0.0118)	(0.0108)	(0.0108)	(0.0079)	(0.0079)
$Treat_f$ * Log-$S1_f$	-0.0941***	-0.0236	-0.0237		
	(0.0267)	(0.0209)	(0.0209)		
$Post_t$	-0.0969***	0.7696***		0.3927**	
	(0.0286)	(0.2534)		(0.1892)	
$Treat_f$	0.3372***	-0.7030*	-0.6994*		
	(0.0649)	(0.4252)	(0.4249)		
Log-$S1_f$	0.4069***	0.0609***	0.0610***		
	(0.0234)	(0.0190)	(0.0190)		
Observations	43,489	43,489	43,489	43,489	43,489
R-squared	0.315	0.708	0.709	0.905	0.906
Firm Controls	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes

Table 4: The Effects of Bank Commitment on Firm-Level Bank Debt and Non-Bank Debt

The dependent variables are *Total Debt*, *Bank Debt*, and *Non-Bank Debt* of firm *i* at year-quarter *t*. A firm is defined as having a committed lender if at least one lender with whom they have a prior credit relationship has committed to reducing emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All models include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)
VARIABLES	Total Debt	Bank Debt	Non-Bank Debt
$Post_{f,t}$* Log-$S1_f$	-0.0190***	-0.0387*	-0.0006
	(0.0068)	(0.0222)	(0.0202)
$Post_{f,t}$	0.1789	0.2076	-0.1086
	(0.2160)	(0.4320)	(0.4325)
$Post_t$ * Log-$S1_f$	-0.0095	-0.0086	-0.0170
	(0.0065)	(0.0184)	(0.0197)
Observations	34,354	34,354	34,354
R-squared	0.914	0.746	0.802
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Table 5: The Effects of Bank Commitment on Total Firm Debt and Maturity

Panel A: Industry and Regional Heterogeneity

The dependent variable in Panel A is *Total Debt* of firm *i* at year-quarter *t*. In each column we introduce a new control to check for robustness. Column (1) is the baseline result. Column (2) uses the more granular 4-digit SIC industry-year fixed effects. Column (3) uses region-time fixed effects. Column (4) includes firm risk, defined as stock volatility times leverage. Column (5) includes intensity rank, defined as a (demeaned) rank of a predetermined firm-level emission intensity within their respective 2-digit SIC industry. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All models include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Total Debt		
$Post_{f,t}$* Log-$S1_f$	-0.0205***	-0.0128	-0.0211***	-0.0142**	-0.0257***
	(0.0075)	(0.0088)	(0.0076)	(0.0069)	(0.0097)
$Post_{f,t}$	0.1299	0.0307	0.1337	0.3101	0.0714
	(0.2071)	(0.2025)	(0.2123)	(0.1889)	(0.2199)
$Post_t$ * Log-$S1_f$	-0.0087	0.0042	-0.0046	-0.0067	-0.0084
	(0.0079)	(0.0093)	(0.0079)	(0.0073)	(0.0100)
$Risk_{ft}$				0.0531***	
				(0.0067)	
$Post_{f,t}$* $Risk_{ft}$				-0.0082***	
				(0.0021)	
$Post_t$ * $Risk_{ft}$				-0.0104***	
				(0.0020)	
$Treat_f$* $Risk_{ft}$				-0.0052	
				(0.0072)	
Intensity $Rank_{ft}$					0.0434
					(0.2640)
$Post_{f,t}$* Intensity $Rank_{ft}$					0.1128
					(0.1237)
$Post_t$ * Intensity $Rank_{ft}$					-0.0066
					(0.1131)
$Treat_f$* Intensity $Rank_{ft}$					-0.1774
					(0.2889)
Observations	43,489	43,442	43,489	39,600	43,489
R-squared	0.906	0.921	0.907	0.922	0.906
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Industry4-Year FE	No	Yes	No	No	No
Region-Time FE	No	No	Yes	No	No

Panel B: Firm-Level Loan Maturity

The regression is estimated at the firm level on an unbalanced panel aggregated from syndicated loans. The dependent variable in columns (1)-(4) of Panel B is the natural logarithm of average firm-level loan maturity within a quarter; in columns (5)-(8) it is an indicator equal to one if the average loan maturity is below the sample median. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Bank controls include ex ante log assets and the tier-1 capital ratio averaged across banks. Lower-level interactions are included but not shown. The regressions in columns 4 and 8 also include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		Maturity				I(Short Maturity)		
$Post_{f,t}$* Log-$S1_f$	-0.0066	0.0093	0.0071	-0.0127	0.0034	-0.0019	-0.0046	-0.0124
	(0.0191)	(0.0217)	(0.0206)	(0.0335)	(0.0133)	(0.0150)	(0.0152)	(0.0224)
Observations	945	945	904	414	945	945	904	414
R-squared	0.031	0.076	0.121	0.725	0.014	0.031	0.040	0.661
Firm Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	No	No	No	Yes	No	No	No	Yes
Time FE	No	No	No	Yes	No	No	No	Yes

Table 6: The Effects of Bank Commitment on Loan-level Estimates

The data are sampled at the borrower-lender-year-quarter level. The dependent variable in columns (1) to (4) is the log value of the credit volume plus one if a lender provides a loan to the firm, and the log of the credit volume in column (5). If a lender has previously participated in a loan to the firm, but does not in the current period, the variables are coded as zero lending for columns (1) to (4), and (6). Column (6) measures only the extensive margin of the loan level (0-1 indicator for whether a firm receives a loan or not). Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Bank controls are ex ante log assets and the tier-1 capital ratio averaged across banks. Lower-level interactions are included but not shown. All regressions include firm-time fixed effects. Columns (4)-(6) additionally include bank fixed effects. Standard errors are double clustered at the firm and bank level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES\ MODEL	Intensive+ Extensive	Intensive + Extensive	Intensive + Extensive	Intensive + Extensive	Intensive	Extensive
$Post_{b,t}$* Log-$S1_f$	-0.0159*	-0.0303**	-0.0239*	-0.0308**	0.0336	-0.0055*
	(0.0091)	(0.0139)	(0.0132)	(0.0136)	(0.0219)	(0.0030)
Observations	60,907	60,907	35,189	60,907	6,964	60,907
R-squared	0.408	0.409	0.513	0.474	0.893	0.476
Firm Controls	No	Yes	Yes	Yes	Yes	Yes
Bank Controls	No	No	Yes	-	-	-
Firm-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	Yes	Yes	Yes

Table 7: The Effects of Bank Commitment on Firm Interest Expenses (Firm-Level Estimates)

The dependent variable is interest expense of firm *i* in year-quarter *t*. In Column (1) a firm is defined as having a committed lender if at least one lender with whom they have a prior credit relationship has committed to reducing emissions. In Column (2) the measure of commitment is the % of a firms' lenders who commit. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All regressions include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)
VARIABLES	Interest Expense	
Commitment Measure	I(Any Bank Commits)	%Committed Banks
$Post_{f,t}$ * $Log\text{-}S1_f$	0.0001	0.0009**
	(0.0001)	(0.0004)
$Post_{f,t}$	-0.0026	0.0035
	(0.0018)	(0.0078)
$Post_t$ * $Log\text{-}S1_f$	0.00005	-0.00002
	(0.0001)	(0.0001)
Observations	38,845	38,845
R-squared	0.552	0.552
Firm Controls	Yes	Yes
Firm FE	Yes	Yes
Time FE	Yes	Yes

Table 8: Real and Financial Effects

The dependent variables are firm-level bank debt and total debt, leverage, total assets, equity, investment (CAPEX), liquids assets (LIQAT), and ROA of firm *i* in year-quarter *t*. A firm is defined as having a committed lender if at least one lender with whom they have a prior credit relationship has committed to reducing emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All regressions include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Bank Debt	Total Debt	Leverage	Assets	Equity	CAPEX	LIQAT	ROA
$Post_{f,t}$* Log-$S1_f$	-0.0411*	-0.0176**	-0.0012	-0.0075**	-0.0072	-0.0150*	0.0009	0.0008***
	(0.0248)	(0.0076)	(0.0011)	(0.0038)	(0.0055)	(0.0085)	(0.0006)	(0.0003)
$Post_{f,t}$	0.2705	0.2147	0.0472*	0.2211***	0.0296	0.0093	0.0030	-0.0010
	(0.4699)	(0.2386)	(0.0257)	(0.0819)	(0.1223)	(0.1846)	(0.0154)	(0.0059)
$Post_t$ * Log-$S1_f$	-0.0085	-0.0109	-0.0010	-0.0074**	-0.0011	-0.0181**	0.0009	-0.0004
	(0.0214)	(0.0076)	(0.0011)	(0.0036)	(0.0052)	(0.0090)	(0.0006)	(0.0003)
Observations	29,354	29,354	29,354	29,354	29,354	29,354	29,354	29,354
R-squared	0.737	0.912	0.837	0.973	0.922	0.881	0.821	0.360
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Environmental Outcomes: Scope 1 Emissions, ESG Score, and Environmental Expenditures

The dependent variables are firm-level pollution, firm commitments to carbon reduction, MSCI ESG scores, and environmental activities, including environmental expenditures, and renewable use. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All regressions include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Log-$S1_{t+1}$	Log-S_{t+2}	Log-$S1_{t+3}$	Log-S1 $_{(t+1, t+2)}$	Log-S1 $_{(t+1, t+3)}$	Committed	ESG Score	Env Score	Env Exp_{t+1}	Env Exp_{t+1}/TA	Renewable
$Post_{f,t}$* Log-$S1_f$	0.0009	-0.0119	-0.0007	0.0011	-0.0046	-0.0004	0.0152	0.0509***	-0.0365	-0.0295	-0.0023
	(0.0121)	(0.0120)	(0.0141)	(0.0130)	(0.0102)	(0.0012)	(0.0100)	(0.0177)	(0.0279)	(0.0914)	(0.0045)
$Post_{f,t}$	-0.3413*	-0.3417*	-0.2331	-0.2770*	-0.2833**	-0.0697***	0.1205	0.6091	-0.1727	0.5980	-0.0263
	(0.1890)	(0.1823)	(0.2246)	(0.1499)	(0.1419)	(0.0234)	(0.1971)	(0.4057)	(0.5437)	(1.1354)	(0.0845)
$Post_t$ * Log-$S1_f$	-0.0301***	0.0015	-0.0056	-0.0237*	-0.0149	-0.0020**	0.0383***	0.0020	-0.0201	-0.0974*	-0.0068*
	(0.0114)	(0.0118)	(0.0082)	(0.0138)	(0.0096)	(0.0010)	(0.0105)	(0.0162)	(0.0197)	(0.0586)	(0.0040)
Observations	9,093	7,244	5,436	7,205	5,375	43,489	32,853	32,853	1,965	1,965	36,488
R-squared	0.970	0.976	0.981	0.982	0.991	0.353	0.846	0.857	0.967	0.736	0.839
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: ESG Score Subcomponents

The dependent variables are firm-level ESG score sub-components of firm *i* in year-quarter *t*. Table 1 provides the definitions of the variables. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All regressions include firm and time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ESG	Env	Soc	Gov	Climate	Natural Res	Waste	Env Ops.	Carbon
$Post_{f,t}$* Log-$S1_f$	0.0152	0.0509***	0.0048	0.0040	0.0475*	-0.0363	-0.0065	0.0789***	0.0078
	(0.0100)	(0.0177)	(0.0187)	(0.0230)	(0.0269)	(0.0243)	(0.0192)	(0.0206)	(0.0248)
$Post_{f,t}$	0.1205	0.6091	-0.3648	-0.3731	0.7335	-0.3785	-0.6945	1.0205**	1.1676**
	(0.1971)	(0.4057)	(0.3491)	(0.4700)	(0.5976)	(0.5699)	(0.4648)	(0.4509)	(0.5592)
$Post_t$ * Log-$S1_f$	0.0383***	0.0020	-0.0254	-0.0458*	-0.0419*	-0.1289***	-0.1760***	0.0383*	-0.0652***
	(0.0105)	(0.0162)	(0.0201)	(0.0273)	(0.0234)	(0.0249)	(0.0206)	(0.0203)	(0.0231)
Observations	32,853	32,853	32,853	32,851	30,337	25,421	24,790	13,841	27,552
R-squared	0.846	0.857	0.761	0.597	0.858	0.801	0.853	0.803	0.875
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Non-Linearities in Carbon Emissions

The dependent variables are firm-level total debt, bank debt, non-bank debt, investment (CAPEX), and log Scope 1 emissions. Quintile 1 represents the firm observations with 20% lowest Scope 1 emission levels and Quintile 5 (omitted baselevel) represents the firm observations with 20% highest Scope 1 emission levels. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. All regressions include firm, time, and size quintile-time fixed effects. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total Debt	Bank Debt	Nonbank Debt	CAPEX	Log-S1
$Post_{f,t}$ * Quintile 1_f	0.1491**	0.4405**	0.0319	0.1713***	0.0553
	(0.0600)	(0.1846)	(0.1736)	(0.0663)	(0.0761)
$Post_{f,t}$ * Quintile 2_f	0.1431***	0.1862	0.1573	0.0735	0.0357
	(0.0517)	(0.1541)	(0.1470)	(0.0558)	(0.0731)
$Post_{f,t}$ * Quintile 3_f	0.1164**	0.0346	0.1696	0.0895*	-0.0103
	(0.0475)	(0.1528)	(0.1358)	(0.0543)	(0.0669)
$Post_{f,t}$ * Quintile 4_f	-0.0033	-0.1418	0.1427	0.0622	0.0526
	(0.0430)	(0.1381)	(0.1408)	(0.0520)	(0.0586)
$Post_{f,t}$	-0.3303	-0.5730	-0.4621	-0.3143	-0.2424
	(0.2693)	(0.5014)	(0.5536)	(0.2288)	(0.1944)
Observations	34,354	34,354	34,354	31,755	34,354
R-squared	0.915	0.748	0.803	0.881	0.969
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Size Quintile-Time FE	Yes	Yes	Yes	Yes	Yes

Table 12: Carbon Emissions at the Bank Level

The dependent variables are the average value of Scope 1 emissions of assets per number of loans (*S1/#Loans*); bank portfolio's Scope 1 carbon footprint relative to the loan volume (*S1/Loan Volume*); the imputed loan weighted Scope 1 emissions, expressed in logs (*WLogscope1*); the imputed loan weighted Scope 1 emission intensity (*Wscope1int*); and bank-level profitability ratio measured by ROA. The main independent variable is $Committed_{b,t}$. The regression models are estimated using weighted least square with weights defined as the loans granted by a bank in a given year. All regressions include bank and time fixed effects. Standard errors are clustered at the bank level. All regressions include bank and time fixed effects. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	S1//#*Loans*	*S1/Loan Volume*	*WLogscope1*	*Wscope1int*	*Bank profits*
$Committed_{b,t}$	0.0309	-0.3642**	-0.0343	-35.8547**	-0.0006
	(0.1003)	(0.1531)	(0.1757)	(16.1758)	(0.0005)
Observations	773	580	773	773	763
R-squared	0.680	0.550	0.631	0.534	0.811
Bank Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Internet Appendix

A. Bank commitments: sample selection

Our starting point of sample selection is the full set of Dealscan institutions in the period of 2013-2018. The vast majority of the financial institutions are banks, but our sample may also include other financial conglomerates with lending arms or other non-bank financial participants in the syndicated loan market.

We combine many data sets with different IDs and definitions of institutions. Dealscan has a CompanyID and ParentID, which gives us lending data and connects to lender ownership. In Dealscan every lender has a CompanyID. We connect lenders through their ownership, which is provided by the UltimateParentID. We use Compustat as a source of financial statement data. Our link is GVKEY, which is similar to ParentID or ISIN.

In Dealscan, when we count financial institutions at the disaggregated LenderUltimateParentID level, we identify 2099 lenders. SBTi sample uses ISIN, similar to ParentID, as an identifier, which is the variable we use to match the data to Dealscan. If a financial conglomerate owns a banking subsidiary who commits to an SBTi target, we treat all lending from institutions within the conglomerate as being committed. According to SBTI 32 institutions make a commitment within our sample. Since SBTi only provides live updates of their signatories these have been confirmed using multiple Wayback machine searches that allows for tracking website at a given point in time. In the raw Dealscan data we can locate 27 of these financial institutions (not found: Actiam, Australian Ethical Investment, Capitas Finance Limited, London Stock Exchange, and Teachers Mutual Bank). Of the 27 institutions, 11 have full information on their balance sheets. Table A1 provides a list of the committing institutions and the dates of their commitments.

Table A1: Bank Commitments

The table reports the list of banks that make commitments to SBTi during the period 2015-2018. We list the names of banks and the dates when each bank makes its commitment. Column 3 indicates which banks can be merged with Compustat database.

Financial Institution	Date Committed	In Compustat
ABN Amro Bank N.V.	Oct-18	Yes
AXA Group	Jun-15	
Allianz Investment Management SE	May-18	
BBVA	Jan-18	Yes
BNP Paribas	Apr-16	Yes
BanColombia SA	Nov-15	Yes
Bank Australia	Nov-15	
Bank J. Safra Sarasin AG	Jun-15	
Commercial International Bank Egypt	Apr-18	Yes
Credit Agricole	May-16	
DGB FINANCIAL GROUP	Jul-18	
Fubon Financial Holdings	Dec-16	
Grupo Financiero Banorte SAB de CV	Oct-16	
HSBC Holdings plc	Jun-16	Yes
ING Group	Jun-15	Yes
La Banque Postale	Oct-17	
MS&AD Insurance Group Holdings, Inc.	Apr-16	
MetLife, Inc.	Apr-16	

Raiffeisen Bank International AG	May-18	
Societe Generale	Apr-16	Yes
Sompo Holdings, Inc.	Jan-18	
Standard Chartered Bank	Jul-18	Yes
Swedbank AB	Nov-18	
TSKB	Jun-15	
Tokio Marine Holdings, Inc.	Mar-18	
Westpac Banking Corporation	Nov-15	Yes
YES Bank	Sep-18	Yes

Table A2: Alternative Proxies of Commitment

This table examines alternative proxies for firm exposure to committed lenders. Column (1) uses an indicator for if any bank the firm has prior relationship with has committed and it is our benchmark case. Column (2) uses the number of banks that have committed as a fraction of the total number of banks a firm has a prior relationship with. Column (3) uses an indicator if any lead bank has committed in which the firm has a prior relationship. Column (4) uses the fraction of lead banks (in which the firm has a prior relationship) that have committed. Each of these variables is interacted with ex ante log emissions demeaned. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)
VARIABLES	Total Debt			
Commit Measure	I(Any Bank Commits)	%Committed Banks	I(Lead Commits)	%Committed Lead
$Post_{f,t}$* Log-$S1_f$	-0.0205***	-0.0952**	-0.0076	-0.0697*
	(0.0075)	(0.0391)	(0.0082)	(0.0397)
$Post_{f,t}$	0.1299	-1.8400**	0.2947	-0.8545
	(0.2071)	(0.7929)	(0.2271)	(0.7906)
$Post_t$ * Log-$S1_f$	-0.0087	-0.0128*	-0.0185**	-0.0175**
	(0.0079)	(0.0074)	(0.0072)	(0.0068)
Observations	43,489	43,489	43,489	43,489
R-squared	0.906	0.906	0.906	0.906
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table A3: Other Emission Measures and Total Debt

This table examines the impact of lender commitment to reducing emissions on firm-level debt, depending on different measures of emissions. Column (1) uses log Scope 1 emissions. Column (2) uses log Scope 2 emissions. Column (3) uses log Scope 3 emissions. Column (4) uses Scope 1 emission intensity, defined as Scope 1 emissions divided by revenues. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)
VARIABLES	Total Debt			
$Post_{f,t}$* $Trucost_f$	-0.0205***	0.0036	0.0075	-0.0001***
	(0.0075)	(0.0100)	(0.0140)	(0.0000)
$Post_{f,t}$	0.1299	0.4014*	0.4257*	0.3268*
	(0.2071)	(0.2085)	(0.2319)	(0.1893)
$Post_t$ * $Trucost_f$	-0.0087	0.0040	-0.0201	-0.0001
	(0.0079)	(0.0091)	(0.0133)	(0.0001)
Observations	43,489	43,489	43,489	43,489
R-squared	0.906	0.906	0.906	0.906
Trucost	Log-S1	Log-S2	Log-S3	S1 Intensity
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table A4: Real and Financial Effects with Intensity Interactions

The dependent variables are firm-level bank debt and total debt, leverage, total assets, equity, investment (CAPEX), liquids assets (LIQAT), and ROA. A firm is defined as having a committed lender if at least one lender with whom they have a prior credit relationship has committed to reducing emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Bank Debt	Total Debt	Leverage	Assets	Equity	CAPEX	LIQAT	ROA
$Post_{f,t}$* Int-$S1_f$	-0.000043	-0.000044***	-0.000005*	-0.000016*	0.000002	-0.000055**	0.000003**	0.000002**
	(0.000058)	(0.000017)	(0.000003)	(0.000010)	(0.000014)	(0.000024)	(0.000001)	(0.000001)
$Post_{f,t}$	0.600484	0.326841*	0.054339**	0.187954**	0.097185	0.126670	-0.010788	-0.008027*
	(0.365262)	(0.189314)	(0.021583)	(0.073917)	(0.098627)	(0.140727)	(0.012698)	(0.004866)
$Post_t$ * Int-$S1_f$	-0.000005	-0.000015	0.000000	-0.000009	-0.000015	-0.000034	-0.000001	-0.000001*
	(0.000044)	(0.000014)	(0.000002)	(0.000010)	(0.000013)	(0.000027)	(0.000001)	(0.000001)
Observations	34,354	43,489	43,489	43,489	42,310	39,973	43,467	40,291
R-squared	0.746	0.906	0.828	0.972	0.929	0.888	0.814	0.344
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Environmental Outcomes with Intensity Interactions

The dependent variables are firm-level pollution, firm commitments to carbon reduction, MSCI ESG scores, and environmental activities, including environmental expenditures, and renewable use. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Log-$S1_{t+1}$	Log-S_{t+2}	Log-$S1_{t+3}$	Log-S1 $_{(t+1, t+2)}$	Log-S1 $_{(t+1, t+3)}$	Committed	ESG Score	Env Score	Env Exp_{t+1}	Env Exp_{t+1}/TA	Renewable
$Post_{f,t}$* Int-$S1_f$	-0.000008	0.000005	-0.000011	-0.000009	0.000005	-0.000008***	0.000057	0.000138***	-0.000086	-0.000381	-0.000003
	(0.000034)	(0.000024)	(0.000025)	(0.000032)	(0.000018)	(0.000002)	(0.000035)	(0.000048)	(0.000053)	(0.000322)	(0.000013)
$Post_{f,t}$	-0.336475**	-0.208919	-0.229043	-0.275269*	-0.209367	-0.070677***	-0.015631	0.171290	0.132329	0.547216	0.002166
	(0.153033)	(0.151686)	(0.177269)	(0.143898)	(0.134620)	(0.019911)	(0.168691)	(0.348029)	(0.438480)	(1.714628)	(0.069092)
$Post_t$ * Int-$S1_f$	-0.000036	-0.000004	-0.000008	-0.000025	-0.000010	-0.000005***	0.000150***	0.000133***	-0.000038	-0.000062	-0.000016
	(0.000029)	(0.000024)	(0.000020)	(0.000023)	(0.000017)	(0.000001)	(0.000037)	(0.000048)	(0.000046)	(0.000122)	(0.000013)
Observations	9,093	7,244	5,436	7,205	5,375	43,489	32,853	32,853	1,965	1,965	36,488
R-squared	0.970	0.976	0.981	0.982	0.991	0.354	0.846	0.858	0.967	0.736	0.839
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Real and Financial Effects – Excluding Oil & Gas

The dependent variables are firm-level bank debt and total debt, leverage, total assets, equity, investment (CAPEX), liquids assets (LIQAT), and ROA. A firm is defined as having a committed lender if at least one lender with whom they have a prior credit relationship has committed to reducing emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. This table excludes firms in the oil and gas industries. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Bank Debt	Total Debt	Leverage	Assets	Equity	CAPEX	LIQAT	ROA
$Post_{f,t}$* Log-$S1_f$	-0.0325	-0.0165**	-0.0020*	-0.0031	-0.0018	-0.0136*	0.0007	0.0007***
	(0.0224)	(0.0077)	(0.0011)	(0.0035)	(0.0050)	(0.0080)	(0.0006)	(0.0002)
$Post_{f,t}$	0.2477	0.1167	0.0331	0.1156	0.0539	0.0023	-0.0032	-0.0000
	(0.4307)	(0.2104)	(0.0245)	(0.0771)	(0.1116)	(0.1619)	(0.0141)	(0.0049)
$Post_t$ * Log-$S1_f$	-0.0078	-0.0090	-0.0008	-0.0078**	-0.0028	-0.0146*	0.0007	-0.0002
	(0.0186)	(0.0082)	(0.0010)	(0.0032)	(0.0045)	(0.0079)	(0.0005)	(0.0002)
Observations	32,486	41,260	41,260	41,260	40,160	37,794	41,239	38,096
R-squared	0.756	0.907	0.837	0.975	0.932	0.894	0.818	0.357
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: The Impact of Borrowers' Commitments

This table examines the impact of the interaction of firm and lender commitments to reduce emissions on various firm-level financial outcomes, depending on their level of emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Total Debt	Leverage	Bank Debt	Assets	Equity	CAPEX	ROA
$Post_{f,t}$ * Log-$S1_f$	-0.0185**	-0.0022**	-0.0404*	-0.0046	-0.0018	-0.0144*	0.0009***
	(0.008)	(0.001)	(0.022)	(0.004)	(0.005)	(0.008)	(0.000)
$Post_{f,t}$ * Log-$S1_f$* NFC $Committed_{ft}$	-0.0705**	-0.0074*	0.0784	-0.0160	0.0082	-0.0385	-0.0004
	(0.036)	(0.004)	(0.097)	(0.012)	(0.013)	(0.027)	(0.001)
$Post_t$ * Log-$S1_f$ * NFC $Committed_{ft}$	-0.0081	-0.0002	-0.0110	-0.0090***	-0.0048	-0.0192**	-0.0005**
	(0.008)	(0.001)	(0.018)	(0.003)	(0.004)	(0.008)	(0.000)
$Post_t$ * NFC $Committed_{ft}$	0.0304	-0.0058	-0.3770**	0.0067	-0.0325	0.0861*	0.0021
	(0.078)	(0.011)	(0.148)	(0.020)	(0.047)	(0.050)	(0.002)
$Post_t$ * Log-$S1_f$	-0.0081	-0.0002	-0.0110	-0.0090***	-0.0048	-0.0192**	-0.0005**
	(0.008)	(0.001)	(0.018)	(0.003)	(0.004)	(0.008)	(0.000)
Observations	43,489	43,489	34,354	43,489	42,310	39,973	40,291
R-squared	0.906	0.828	0.747	0.973	0.929	0.888	0.344
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A8: Loan-Level Analysis: Robustness

This table analyzes the robustness of the main loan level results. The data is at the borrower-lender-year-quarter level and the tables follows Table 5. Columns (1)-(4) examine the extensive and intensive margins of lending together. Column (1) adds more stringent Bank-Time fixed effects. Column (2) employs a Poisson model. Column (3) adds an indicator control for whether a lender was a prior lead lender for that firm. Column (4) controls for the length of the firm-bank relationship. Firm controls are interacted with bank commitment. Standard errors are double clustered at the firm and bank level. ***p<.01, **p<.05, *p<.1.

VARIABLES	(1) Intensive + Extensive	(2) $ Intensive + Extensive	(3) Intensive + Extensive	(4) Intensive + Extensive
$Post_{b,t}$* Log-$S1_f$	-0.0286**	-0.0340*	-0.0315**	-0.0269*
	(0.0145)	(0.0203)	(0.0137)	(0.0141)
Observations	58,695	15,733	60,907	60,907
R-squared	0.509		0.474	0.478
Robustness	Bank-Time FE	Poisson	Prior Leader	Relation Length
Firm Controls	Yes	Yes	Yes	Yes
Firm-Time FE	Yes	Yes	Yes	Yes
Bank FE	-	Yes	Yes	Yes

Table A9: The Effects of Bank Commitment on Loan-level Estimates (Full Sample of 27 banks)

VARIABLES	(1) Intensive +Extensive	(2) Intensive	(3) I(Loan)
Committed*Log-$S1_f$	-0.0156*	0.0270	-0.0039*
	(0.0080)	(0.0180)	(0.0021)
Observations	89,312	10,022	89,312
R-squared	0.476	0.905	0.477
Bank Controls	No	No	No
Firm Controls	Yes	Yes	Yes
Firm-Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes

Table A10: Non-Financial Company Commitments and Environmental Outcomes

This table examines the impact of the interaction of firm and lender commitments to reduce emissions on firm-level pollution and other environmental activities depending on their level of emissions. Firm controls are ex ante log total assets and revenue growth interacted with $Post_{f,t}$, $Treat_f$, and $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

VARIABLES	(1) ESG	(2) Env Score	(3) Soc Score	(4) Gov Score	(5) Climate Score	(6) Natural Resource Score	(7) Waste Mgmt Score	(8) Env Opps Score	(9) Carbon Score	(10) Log-$S1_{t+1}$	(11) Env Exp_{t+1}	(12) Renewable Use
$Post_{f,t}$ * Log-$S1_f$	0.0136	0.0473***	0.0008	0.0090	0.0492*	-0.0364	-0.0068	0.0774***	0.0073	0.0025	-0.0304	-0.0029
	(0.0100)	(0.0179)	(0.0187)	(0.0231)	(0.0272)	(0.0243)	(0.0191)	(0.0210)	(0.0252)	(0.0122)	(0.0929)	(0.0045)
$Post_{f,t}$ * Log-$S1_f$* NFC $Committed_{ft}$	0.0693	0.1478***	0.1453**	-0.1467	-0.0651	0.0184	0.0411	-0.0026	-0.0573	-0.0514	0.1392	0.0129
	(0.0449)	(0.0566)	(0.0718)	(0.1090)	(0.0741)	(0.0977)	(0.1116)	(0.0599)	(0.0627)	(0.0443)	(0.1520)	(0.0139)
$Post_t$ * Log-$S1_f$ * NFC $Committed_{ft}$	0.0102	-0.0056	-0.0726	0.1889	0.0066	0.0449	0.0762	-0.1430	-0.1808	0.0712	0.1567	-0.0531
	(0.1211)	(0.1989)	(0.2153)	(0.3007)	(0.2409)	(0.3138)	(0.2220)	(0.1778)	(0.1485)	(0.1003)	(0.2394)	(0.0355)
$Post_t$ * NFC $Committed_{ft}$	-0.0021	-0.0906	0.1247	-0.4100	0.0666	0.1460	-0.0136	0.0321	-0.1797	0.0472	0.1640	-0.0011
	(0.1119)	(0.1708)	(0.1757)	(0.3606)	(0.2157)	(0.2871)	(0.2407)	(0.1821)	(0.1273)	(0.0685)	(0.1897)	(0.0283)
$Post_t$ * Log-$S1_f$	0.0378***	0.0002	-0.0254	-0.0482*	-0.0407*	-0.1273***	-0.1765***	0.0385*	-0.0672***	-0.0294**	-0.0965	-0.0069*
	(0.0106)	(0.0163)	(0.0202)	(0.0273)	(0.0235)	(0.0247)	(0.0209)	(0.0206)	(0.0233)	(0.0115)	(0.0588)	(0.0040)
Observations	32,853	32,853	32,853	32,851	30,337	25,421	24,790	13,841	27,552	9,093	1,965	36,488
R-squared	0.846	0.857	0.761	0.597	0.858	0.801	0.854	0.804	0.875	0.970	0.736	0.839
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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ECGI is an international non-profit membership organisation that provides a platform for debate and dialogue among academics, policymakers, and business leaders, with a focus on major corporate governance, ESG, and stewardship issues.

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