Carbon Emissions and the Bank-Lending Channel

Finance Working Paper N° 991/2024
July 2024

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ECGI Working Paper Series in Finance

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We thank for helpful comments Viral Acharya, Allen Berger, Patrick Bolton, Michel Habib, Raj Iyer, Andrew Karolyi, Raghu Rajan, Michael Roberts, Zach Sautner, Philip Strahan, Qifei Zhu, and seminar participants at Bank of England, Bank of Greece, Bank of Italy, Bank of Spain, Carnegie Mellon University, Cornell University, Danmarks Bank, EBRD, Erasmus Rotterdam, ESSEC, European Commission JCR, Florida International University, Goethe University Frankfurt, Imperial College, Moscow Finance Conference, IWH, LSE, NBER Summer Institute, Norges Bank, Northeastern University, RFS-Energy and Climate Finance Conference, Tulane University, UNPRI, University of Chicago, University of Frankfurt, University of Lugano, University of Michigan, University of South Carolina, University of Warwick, University of Zurich, the U.S. Treasury, and Virtual Research Seminar. We especially thank Andrea Fabiani and Win Monroe for excellent research assistance and numerous suggestions.

Abstract

We study how firm-level carbon emissions affect bank lending and, through this channel, real outcomes in a sample of global firms with syndicated loans. We use bank-level commitments to decarbonization to proxy for changes in banks' green preferences and, via these commitments, shocks to firms with previous credit from these banks. Firms with higher carbon footprint previously borrowing from committed banks subsequently receive less bank credit. Affected firms also lower their total debt, leverage, size, and real investments, and increase their liquid assets. We find no improvement in environmental performance of brown firms, but only evidence consistent with firms' greenwashing.

Keywords: carbon emissions, bank lending, cost of debt, real effects, environmental performance

JEL Classifications: G12, G23, G30, D62

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1. Introduction

The battle against global warming is at the forefront of social and policy debates. A fundamental element to mitigate the climate problem, supported by strong scientific evidence, is the reduction of carbon emissions, especially those of the private sector, a process that is often described as decarbonization. For the process to succeed it requires a strong involvement of many economic players, from the public and private sectors, including the financial sector (see, Bolton, Hong, Kacperczyk, and Vives, 2021, or Giglio, Kelly, and Stroebel, 2021), both in terms of capital provision and disciplinary actions to facilitate environmental progress.

Of special importance in the decarbonization process is the banking sector, given its centrality in allocating resources to non-financial companies (NFCs), its ability to impose costs on non-compliant companies either through quantity or price adjustments, and its power to coordinate actions. Unlike capital markets which mostly affect publicly listed companies, banks reach a broader scope of economic and geographic activity, including both public and private firms. Finally, while banks may be somewhat slower in responding to social and policy pressure, conditional on taking actions, they are more likely to maintain their discipline due to higher adjustment costs (selling a loan versus selling a listed share).

While the involvement of the banking sector is growing, it is fair to say that the decarbonization process in the banking sector is in its early stages and evidence in the aggregate suggests that banks still support a large production of carbon emissions. Since 2015, 60 major banks have, for example, allocated $4.6 trillion into fossil fuel industry, including $742bn into oil, gas, and coal in 2021 alone. At the same time, more and more banks come under pressure or decided themselves to become involved in the process of decarbonization. For example, some Central Banks (e.g., Bank of England or ECB) have recently been discussing guidelines regarding capital requirements against potential climate-related losses, including encouraging banks to measure and disclose their exposures to climate-related risks through stress tests for banks. Moreover, banks themselves get involved in various climate actions, with the Net-Zero Banking Alliance launched in April 2021 being one of the most prominent initiatives.[1]

It is thus an empirical question whether their role in the decarbonization process is meaningful. Do banks enforce emission reduction, by actively cutting credit to brown firms and (possibly) channeling credit towards green firms or do they provide credit to brown firms for investment to reduce carbon emissions? Alternatively, are banks' actions a form of cheap talk without any real change? Importantly, do banks' actions lead to improved environmental performance of real sector responsible for carbon footprint? Answering these questions is paramount as has been for example highlighted by policy makers, including, among others, the then Bank of England's Governor, Mark Carney (2015) and the European Central Bank's President, Christine Lagarde (2019).

In this paper, we shed light on these issues by looking at a sample of global firms that rely on bank credit and exhibit a rich cross-sectional variation in their carbon emission levels. We study how firm-level carbon emissions affect bank lending and, through this channel, real, financial, and environmental outcomes. As an empirical identification strategy of banks' willingness to reduce brown lending, we exploit a cross-sectional variation among banks on whether they commit (or not), through the Science Based Targets Initiative (SBTi),[2] to a well-defined path of reductions in carbon emissions of their asset portfolios. The extent to which such commitments result in a more environmentally friendly distribution of credit across firms is ex ante unclear. In the absence of sharp penalties and tight rules on lending to brown firms, commitments might be a tool for greenwashing, resulting in small or nil implications for the allocation of credit. Importantly, the bank commitments are shocks to firms with prior lending relationships with these banks. Moreover, even if banks making commitments change their lending behavior, it is not clear whether firms could not get their funding through other financial intermediaries and instruments, and hence continue

[1] As of March 2022, the Alliance includes 106 members from 40 countries, representing $68 trillion, or 38%, of global bank assets.
[2] Even though SBTi is not the only initiative to coordinate climate actions, it is one of the most powerful ones, with the endorsement of several socially important figures, such as Michael Bloomberg, Mark Carney, or Angela Merkel.

polluting and investing. As such, we also analyze the credit supply mechanism via firm- and loan-level data.

We analyze firm-level scope 1 emissions, which we measure at the start of our sample before any commitment. Scope 1 greenhouse gas (GHG) emissions occur from sources that are controlled or owned by a firm. Scope 1 emissions are not only related to commitments in SBTi but are also easier to measure.[3] In our sample of firms, a standard deviation of the cross-section of scope 1 emissions equals 15.8 million tons of CO2e. On the pure cross-section of firms, the coefficient of variation with the median is around 50 and the firm in the 75th percentile of the empirical distribution has 13 times higher pollution than the one in the 25th percentile. To deal with such a highly non-linear distribution of scope 1 emissions, we take logs though the variation remains large, with the standard deviation being 2.5.

In our first test, we examine whether firms associated with banks that decide to make commitments experience different financing outcomes, conditional on their level of scope 1 emissions. We analyze staggered commitments to the SBTi-targets by financial institutions with large exposures in the syndicated loan market (these committing banks participate in 60% of the loans). Our data cover the 2013-2018 period, reflecting the fact that the first SBTi commitments happen not earlier than in mid-2015. We define firm exposures to banks based on their prior connections established from 2000 to 2012, thus alleviating potential concerns of the selection of firms to committing banks. Our setting lends itself to estimating a staggered difference-in-differences regression model, in which we compare outcomes across firms: i) before and after bank commitments; ii) depending on whether firms have, or do not have, previously credit with a committed bank; iii) conditional on whether a firm is relatively green, or brown, based on its prior level of greenhouse gas (GHG) emissions.

[3] Scope 2 emissions relate to the purchase of electricity (and steam and heat), and scope 3 emissions originate within the value chain in which a company operates. Details on the precise definitions of emissions are provided in the Greenhouse Gas Protocol.

Our results provide strong and robust evidence that committed banks affect firms' credit outcomes, conditional on the level of their emissions. The effect is present in both low-emission (green) firms, which are allocated relatively more credit, and in high-emission (brown) firms, which experience a reduction in total credit. Specifically, after a bank commits to carbon emissions reduction, firms with higher ex-ante scope 1 emissions and with prior (to our sample) credit with the committed bank (thereafter, "committed" firms) experience a relative reduction in total debt from all financing sources, compared to firms with the same levels of emissions but without ex-ante lending connections to the committed bank. The effect is economically significant with the difference in total debt of 6.4 percent per one-standard-deviation change in cross-sectional emissions. In turn, we do not find significant evidence on total debt based on the variation in levels of scope 2 and scope 3 emissions. The distinction in results between the two types of emissions likely reflects the fact that banks in our sample only commit to reductions in scope 1 emissions as these emissions are easier to track and attribute to specific firm actions. In sum, our results indicate that committed firms obtain less financing and do not fully substitute their reduction in financing from committed banks with borrowing from other banks or nonbanks.[4]

We provide further evidence on the source of the financing effect using several additional tests. We first divide firms' total debt into bank debt and non-bank debt and find that the effects for total debt are 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, within 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

[4] Interestingly, results suggest that the credit reallocation from brown to green is partly across industries, even in the same period, and partly within the same industry in the same period. Consistently, all results are robust to excluding key industries such as oil and gas that suffered a negative shock in 2014-16.

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, CO2 emissions, or risk, leverage, or revenues. Finally, the results satisfy the test of omitted variables and selection on unobservables based on Oster (2019) and Altonji et al. (2005), that is, in the process of sequentially controlling for a large number of observables and different sets of fixed effects (e.g., firm observable controls, firm-fixed effects, time-fixed effects, industry-time-fixed effects, or region-time fixed effects) that massively increase the debt regression R-squared (by 60 percentage points (pp)), estimated effects remain very similar.

In our subsequent tests, we shed more light on the underlying economic mechanism driving bank financing decisions. We consider two possible hypotheses. In the first one (*risk-management hypothesis*), risk-averse banks cut credit to high-emission firms and channel credit to low-emission firms if they recognize that financial risk associated with firm operations positively correlates with their emission activity. In this regard, banks' decisions simply manifest their prudent approach to lending. An alternative *preference hypothesis* postulates that committing banks make their credit decisions also taking into consideration their preferences for green versus brown assets and potential reputational concerns imposed by their stakeholders. To distinguish between the two hypotheses, we perform three tests. First, we directly control in our regressions for measures of credit risk based on the degree of firm leverage and its underlying stock return volatility. Our effect retains its economic significance after controlling for financial risk, even though financial risk also matters for credit allocation.[5] Quantitatively, committed firms with a one-standard-deviation higher scope 1 emissions experience credit cut by 5.1 percent (as compared to uncommitted firms), whereas the overall effect without controlling for firm risk is 6.4 percent. Second, to assess the relative merits of the two channels, we look at relative changes in debt maturity choices. If bank behavior was an outcome of climate risk management, one should expect loan maturity to reduce given that

[5] Our proxy for firm risk is rolling stock-return volatility (lagged by one quarter), multiplied by firm financial leverage (debt over total assets). For this test, the risk measure is included in the baseline regression model by interacting it with the same treatment and time variables as scope 1 emissions.

financial risk via climate risk is mostly related to medium and long-term events. Our results indicate no significant change in maturity choices, the result that is more consistent with the preference hypothesis.

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. At a broad level, we can absorb firm-year-quarter fixed effects in our regressions and thus we can study lending decisions from committed vs. non-committed banks to the same firm at the same time, going in the direction of isolating a credit supply force. Here, we analyze 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.[6] 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 further supports the preference story along the lines of the divestment channel we observe in capital markets (e.g., Hong and Kacperczyk, 2009). 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 (while at the same time lower volumes), consistent with a credit supply channel. The price effect, however, is economically weaker than the quantity effect, which is consistent with the stated preference for portfolio decarbonization in bank commitments.

Overall, the results on the lending front suggest that committing banks do impose restrictions on polluting firms and reallocate funding towards greener firms, and that other financing sources, such as uncommitted banks and non-bank debt, are not perfect substitutes for the affected firms.

[6] 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.

While the increased restrictions to access credit may adversely affect polluting firms, the question is whether such firms' corporate decisions internalize the banking force. To answer this question, we investigate firm-level real 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 leverage, investment, and asset size. A one-standard-deviation increase in ex-ante scope 1 emissions leads to a reduction in *CAPEX* of brown firms by 4.3 percent and in total assets by roughly 2 percent. We further observe that firms increase the size of their liquid assets, which is consistent with the hypothesis that the loss of financial flexibility leads to greater cash hoarding. The real effects are non-linear in that we observe a relatively strong cut (increase) in bank lending and investment to most (least) polluting firms, with mild effects in between these extremes. The above results are consistent with predictions coming from models of real and financial decisions by firms facing financial inflexibility (e.g., Bolton et al. 2019). As an auxiliary prediction, we also observe an increase in average profitability of firm assets (ROA), which suggests that the projects that brown companies cut are less profitable.

The above results suggest that firms do respond to bank pressure. However, the ultimate and socially most important question is whether such firms adjust their environmental performance consistent with the committed banks' preference. On the one hand, affected firms have significant incentives to become relatively greener, as this grants easier access to bank financing; on the other hand, the tightening of credit standards due to SBTi commitments might limit their ability to invest in green technology or it may be costly to do so. Also, firms may be reluctant to cut their investment in carbon-intensive projects if such projects have higher profit margins.

Despite firm-level real and financial effects associated with bank commitments for browner firms, we do not find any reduction in carbon emissions over one year, which represent hard data (and choice). Since adjustment of environmental performance may be a slow process, we also analyze whether affected firms change their emissions significantly over the longer horizon of up to 3 years, or whether they at least express their willingness to commit to future emission reduction, using again SBTi commitments as a relevant proxy. Again, we do not find any significant incidence that emissions change in the longer horizon or that firms change the intensity of their commitment efforts.

However, we find that committed firms with higher emissions significantly improve their environmental MSCI *E*-scores, although by just 10 basis points as a response to a one-standard-deviation higher scope 1 emissions. When we decompose the *E*-score into its subcomponents, we do not find any evidence of significant changes in environmental expenditures. Instead, what drives the improvement in environmental (ESG) performance is better communication of future environmental opportunities. 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. Our results suggest that committed banks perceive these efforts as non-credible given that we observe a significant cut in credit (i.e., it is consistent for committed banks to cut their credit to the brown firms as, on average, these firms do not relatively become ex post less brown). These results also reflect banks' adherence to their SBTi commitments which are strictly about portfolio decarbonization. Further, we find that the lending pressure on affected firms does not change materially even if firms commit to future emission reductions.

Overall, our results suggest that banks affect carbon emissions via credit reallocation (from brown to green firms) rather than via providing loans to brown firms for the investment necessary to reduce carbon emissions.

Contribution to the literature. Our paper contributes to the recent and flourishing literature on climate finance.[7] By now, relatively large evidence exists that investors ask for a premium to hold stocks of firms highly exposed to climate risk (e.g., because of high level of carbon emissions, as in Bolton and Kacperczyk, 2021abc), especially during periods in which climate risk is perceived to be higher (Engle et al., 2020; Choi

[7] For a review of this literature, see Giglio et al. (2021).

et al., 2020). Similarly, corporate bonds issued by firms highly exposed to climate risk are found to generate lower future *ex-post* returns, amplified by perceptions of increased climate risk (Huynh and Xia, 2020; 2021). Our paper contributes to the literature by showing the bank-lending channel for carbon risk.

The literature on the implications of climate change for banking is rather sparse. Few papers analyze how loan pricing responds to firm exposure to carbon risk through carbon emissions (Delis, de Greiff, and Ongena, 2019; Degryse et al., 2021; Ehlers, Packer, and de Greiff, 2021). Gingingler and Moreau (2019) and Nguyen and Phan (2020) show that greater exposure to climate risk is associated with a reduction in corporate financial leverage. Using loan-level data, Reghezza et al. (2021) show that bank lending gets reduced after the Paris Agreement. We make several contributions to this literature. First, unlike the other papers, we consider the full bank-lending channel related to carbon risk in that we not only focus on the allocation of credit across firms with different levels of exposure to climate risk through carbon emissions but, importantly, we document that committed banks cut credit supply to firms that pollute relatively more, with significant firm-level real effects (e.g., firm investment, total assets). Despite the real and financial effects, we find no improvement in hard firm-level environmental scores for brown firms, but only evidence consistent with firm greenwashing. Second, we show that corporate deleveraging is due to bank-lending channel, prompted by a change in banks' preferences towards lending to green-*vs*-brown firms, rather than by a financial risk factor. Third, we are also the first to show explicitly the role of bank environmental commitments in their lending activity and its transmission to the real sector, including their impact on carbon emissions. Fourth, we show that banks affect carbon emissions via credit reallocation (from brown to green firms) rather than by improving brown firms' provision of capital for green investments.

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

2. Data

Our main analysis covers a sample of international firms for the period 2013-2018. The data we use result from merging the following sets: syndicated lending relationships from Thomson Reuters Dealscan; firm-level GHG emissions from S&P Global Trucost; and firm-level information (e.g., firm investment, size, output, leverage, or return volatility) from Compustat Global. Information from Compustat Global is matched with Dealscan following the methodologies in Chava and Roberts (2008) for non-financial companies (NFCs) and Schwert (2018) for lenders. We match Trucost data with the rest using ISIN. The combined data is a sample of 2113 firms, of which 630 firms have their headquarters located in the US, 347 in the European Union, 191 in the UK, and the remaining 945 firms are located elsewhere. We also use firm-level information from Capital IQ on firm-level finance from banks versus nonbanks, from MSCI on ESG ratings, and on firm-level environmental expenditure from Refinitiv. We report all summary statistics in Table 2.

In our empirical strategy, we utilize the data on bank commitments, following the Science Based Targets initiative (SBTi).[8] For some tests, we also identify NFCs which directly commit to SBTi. The SBTi is a joint initiative by Carbon Disclosing 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. In the context of banks, this means greening their asset portfolios rather than reducing carbon footprint of banks which generally is quite small. Specifically, Article 2.1(c) of the Paris Agreement states the objective as "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development."

[8] Bolton and Kacperczyk (2021d) provide more details on the origins of SBTi and the drivers of participation therein.

The SBTi now comprises just over 1000 companies in 60 countries, with a combined value of $20.5 trillion.[9] 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. Banks generally do not specify the horizon of their portfolios' greening and their commitments concern scope 1 emissions only.

Our full sample includes 27 banks that either committed or stated a target for emission reductions. We list the banks in Table A1 of the Appendix.[10] These committed banks participate in approximately 60% of the loans. Notable names include BBVA, BNP Paribas, Credit Agricole, HSBC, ING, Societe General, and Standard Chartered. In general, banks commit 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. 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, and $Committed_b = max_b(Post_{b,t})$, which is equal to one if bank *b* ever commits to SBTi during our sample period.

Bank commitments are not random, are a choice for banks and largely depend on the business environment in which banks function. Anecdotally, banks commit to SBTi because various stakeholders exert pressure on them to do so. The stakeholder pressure is generally multi-dimensional and includes climate policy strictness, the equity ownership structure, media sentiment, customer relations, or board characteristics. We provide some characterization of each of the channels using the following proxies. For

[9] See "From Ambition to Impact: Science Based Targets Initiative Annual Progress Report 2020."
[10] For our baseline regressions, we use a restricted sample of eleven banks making commitments because the remaining banks are missing in Compustat, which is a source of additional controls. However, for robustness, we also evaluate our results in the setting without such controls using the full sample. The results based on this sample are qualitatively very similar (though in this case we cannot control for bank characteristics or analyze differences in bank fundamentals).

climate policy pressure we use the country-level measure of climate risk index (*CRI*) obtained from Germanwatch. To analyze the role of ownership structure we look at both the level and concentration of institutional ownership. Institutional ownership (*IO*) is the percentage level of bank ownership that is held by institutional investors. Ownership concentration (*TOP 5*) is defined as a fraction of bank shares that is held by five largest institutional owners. Both measures come from Thomson Reuters database. We hypothesize that institutional pressure should increase with the increase in both level and concentration of ownership. For the measure of media pressure, we use the positive slant of media coverage (*ESS*) which we obtain from Ravenspack. We posit that banks which are subject to greater media pressure, or face less positive coverage, should be more likely to make commitments. For client loyalty, we use the score that measures the loyalty of the bank clients (*LOYALTY*). Finally, to capture the role of board pressure we use board size (*BOARD*) defined as the number of board members sitting on a bank's board. The last two variables are obtained from Refinitiv.

We relate each of the stakeholder pressure variables to the likelihood of bank commitments, by estimating the following regression model, in which we iteratively enter each of the pressure variables as well as different fixed effects, all measured at the annual frequency.

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

Our first specification includes year and country fixed effects to capture the cross-bank variation in commitments, while our second specification replaces country fixed effects with bank fixed effects to capture any within-bank time-independent variation that may predict commitments. In all regressions, we double cluster standard errors by country (bank) and year. We report the results in Table 1.

We find that in the cross-section of banks (columns 1-6), institutional ownership and customer loyalty are positively related to bank commitments. Also, larger investor concentration and board size predict bank commitments, but these effects are statistically insignificant. Positive media sentiment, in turn, is negatively related to bank commitments though insignificant. All the results are qualitatively consistent with our hypotheses. When we further account for bank fixed effects (columns 7-11), we find that even though the signs of all coefficients remain unchanged, customer loyalty and board size are the only two coefficients that remain statistically significant.[11]

An important step in our analysis is establishing which firms are connected, through prior credit intakes, to banks which are committed to green 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; i.e., the ex-ante connection means any connection prior to 2013 (the start of our sample). For instance, the generic couple of firm f and bank b is defined as connected in quarter t if firm f has ever borrowed from bank b up to t 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. Formally, let B_f be 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 previous lenders, and zero before. Committed firms are those whose lenders eventually commit, that is, those for which the indicator variable $Treat_f$ equals one.

Summary statistics in Table 2 suggest that more than 60% of the NFCs in our sample are connected to committed banks. This large share reflects the fact that committed banks are very active institutions in the syndicated loan market. To explore additional variation in lending arrangements, we define other variables to capture the strength of such relationship. First, we identify lead banks (or 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; 52% of firms in our sample have a lead-arranger committed to SBTi. Second, for our connection indicator, and its lead-bank counterpart, we construct an intensive-margin proxy, namely, the share of lenders

[11] Importantly, committed versus other banks do not differ in their lending portfolio toward brown firms, or to firms in brown sectors that suffer negative shocks (oil and gas).

(*%Committed*$_f$) and the share of lead-arrangers (*%LeadCommitted*), out of the total number of firms' lenders committed to SBTi. On average, 15% and 12% of the total number of lenders involve committed banks and committed lead-banks, respectively. Importantly, as explain in the section, we also exploit the time variation, that is, before and after a bank commits, and not only the cross-sectional variation.

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, because within our sample banks have only made commitments with regard to this type of emissions. As the first bank commitment happens in mid-2015 and our aim is to rely on ex-ante measures of firm pollution, 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 (i.e. before any commitment), expressed in tons of emissions and denoted as $S1_f$.

Indeed, our sample features a highly heterogenous and skewed distribution for $S1_f$, as presented in Table 2. The average firm produces roughly 3.56 million tons of emissions per year. Moreover, a cross-sectional standard deviation of $S1_f$ equals 13.8 million tons. On the cross-section of firms, the coefficient of variation with the median is around 50 and the firm in the 75th percentile of the empirical distribution has 13 times higher pollution than the one in the 25th percentile (there numbers are around 100 and 30 if we take all the variation of scope 1). To deal with such a highly non-linear distribution of scope 1 emissions, we take the natural logarithm of $S1_{f,pre,}$ obtaining the relatively more normally distributed variable, $LogS1_f$. Further, to facilitate a better interpretation of our coefficients, we demean $LogS1_f$; its distribution is summarized in Table 2. Despite the logs, the cross-sectional variation of scope 1 is still large, e.g. the standard deviation is 2.5.

For some of our empirical tests we use financial variables. The mean outstanding total debt in our sample of firms corresponds to $1276 million, with notable differences across firms. 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. 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 10.5 pp and an associated standard deviation of 8.6 pp. We also study other financial variables, in particular leverage equity, and liquid assets summarized in Table 2.

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 scores and its environmental subcomponent. Both sets variables take on values ranging from 0 (worst) to 10 (best). For both variables, the average firm has a score close to 5 points, with a standard deviation of close to 2 points. In practice, the ESG score is computed as a weighted average of its three main subcomponents, which, in turn, are obtained as a weighted average of further (sub)subcomponents. For the *E* subcomponent, 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. These represent a very small, close to 1%, fraction of total assets.

Finally, to better dissect 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 is either at the extensive, intensive, or at both margins of lending. In particular, on the extensive margin, for a given firm in a given quarter, the set of (potential) lenders includes all banks involved in previous loan syndicates with that firm, in addition to any new lenders for the new loan issued in that quarter. We investigate whether a bank lends to that firm in that quarter (an indicator variable). On the intensive margin, we analyze credit volume granted by each lender that lends to the firm in that quarter. Finally, we combine the extensive and intensive margins, in that we analyze scenario in which some banks do not provide loans (value equal to zero), while other banks provide positive credit volume.

3. Empirical Strategy

Our empirical strategy exploits the fact that some banks commit to SBTi. We use these commitments in two ways. First, as differential bank preferences for brown/green to answer the question whether they are associated to subsequent material changes in bank lending strategies, or are simply a manifestation of (bank) greenwashing. Second, as a tool for empirical identification. We can think of banks' commitments as shocks to firms that ex ante (prior to our sample) borrowed from these committed banks, and we can analyze their impact on various corporate outcomes. Our sample is over 2013-2018 and the links between firms previously borrowing from banks are from 2000 to 2012. As shown later, we also test for selection on firm observables and unobservables driving the results and test for parallel trends. Our main empirical specifications study the implications of these bank commitments for different firm-level outcome variables, $y_{f,t}$, such as debt (total debt, bank debt, non-bank debt, leverage), real effects (e.g., total assets, liquid assets, CAPEX, and ROA), and environmental effects (e.g., environmental score, carbon emissions, and environmental spending). Formally, we estimate the following staggered difference-in-differences model:

$$y_{f,t} = \beta_1 \text{LogS1}_f + \beta_2 \text{Treat}_f + \beta_3 \text{Post}_t + \beta_4 \text{LogS1}_f{*}\text{Treat}_f +$$

$$\beta_5 \text{LogS1}_f{*}\text{Post}_t + \beta_6 \text{Post}_{f,t} + \beta_7 \text{Post}_{f,t}{*}\text{LogS1}_f + \theta_1 \text{Controls}_f + \text{FE} + e_{f,t} \qquad (2)$$

In the above equation, $Post_t$ is an indicator variable that equals to one from 2015Q2, the first date in which banks commit to SBTi, onwards. We include this variable to capture the counterfactual response to commitment events for the control group. Moreover, through the coefficient β_5 we also control for the possibility that firms with greater levels of scope 1 emissions may have in general recorded lower profitability (or higher risk) after the date of the first commitment (for instance coinciding with the Paris Agreement, exerting a general pressure to decarbonize),[12] thereby experiencing different dynamics in both debt and investment.

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 assets size. Both variables are fully interacted with $Treat_f$ and the *post* dummies. In the Appendix, we show that size is the only firm observable which is different between committed and non-committed firms. Once we control for size, carbon emissions, sales growth, total debt, risk, and leverage are not different statistically or using normalized differences (see Appendix, Table A2).[13] We also analyze the Oster (2019)'s test on selection of unobservables and results suggest that omitted variables and self-selection are not driving the significant effects (please see the details of this analysis in Section 4). Additionally, *FE* represent various sets of fixed effects, which, in the most robust version of the model, are set along the time and firm dimensions: the former absorbs any variation which is common across all firms; the latter takes care of within-firm time-

[12] Or for instance due to a reduction in oil and gas prices around 2015. Note that nevertheless our results are stemming from both within and between industries, and moreover our results are robust to excluding firms from the oil and gas sectors.
[13] For an explanation of normalized differences, see Imbens and Wooldridge (2009).

invariant (observed and unobserved) heterogeneity.[14] For robustness, we also control for industry-time and region-time fixed effects (and in the loan-level data for firm-time and bank-time fixed effects). $e_{f,t}$ represent error terms, which we cluster at the firm level in the firm level regressions, in line with the fact that the key coefficient of interest is identified by firm-level heterogeneity (Cameron and Miller, 2015) and the data are oriented at the firm-time level.

Equation (2) represents a model with staggered treatment across firms. The key identification assumption for consistently estimating β_7 is that, absent bank commitment, connected and unconnected firms with comparable levels of scope 1 emissions would have experienced parallel dynamics in their bank debt. Put differently, consistently estimating β_7 requires an augmented version of the parallel trend assumption to hold. The challenge with respect to a standard difference-in-differences model with common time treatment is that, given staggered commitment across banks, there is not a single time period in which the treatment effect should materialize, thereby complicating the usual pre-*vs*-post comparisons.[15] In our setting, there are in fact more than one date when banks commit. Hence, to inspect the parallel-trend assumption, we estimate equation (2) separately for committed and uncommitted firms (that never commit in our sample period), in particular we estimate the impact of scope 1 in each time period (see Figure 1). For uncommitted firms, estimated coefficient of scope 1 should be generally insignificant. In turn, for committed firms, that is, those connected prior to our sample (through syndicated loans) with committed banks, under the hypothesis of non-greenwashing by banks and cut in bank lending being binding, the estimated coefficient may be negative after 2015Q1, with a potential effect also showing up in 2016Q2 when other large set of commitments occur.

To further investigate the credit-supply mechanism, we conduct several additional tests. First, we use the Oster (2019)'s test for the selection on unobservables (i.e., is the unobserved covariance between

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[14] Under the version of 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. Note that firm-level emissions are measured before any commitment and are not time varying.
[15] For a formal explanation, see Goodman-Bacon (2021).

post f,t * scope 1 *and* firm observables and fixed effects changing the estimated coefficient on total debt?). Second, we divide firm total debt into bank debt and non-bank debt and analyze each component. Third, we analyze the average loan rates that firms pay (that is, we analyze both total debt volume and average interest payments). Fourth, we conduct a loan-level analysis with firm-time fixed effects in which we examine the lending volume of committed banks vs. other banks to the same firm in the same quarter for a given level of firm emissions. All these results are discussed in Section 4.

4. Results

In this section, we provide our empirical findings. We first report several results related to bank 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

Table 3 reports findings for the estimation of equation (2), with (log) total debt as the dependent variable. We present results under progressively saturated versions of the model. In column 1, we do not include 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–that control for changes in firm debt which are common across all firms in our sample–and firm-fixed effects, which take care of firm-level time-invariant heterogeneity. Finally, in column 5, we integrate 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 -0.025) and statistically significant at conventional levels (e.g., at the 1% level in the most saturated regression model, in column 5).

To assess the economic magnitude of the described effects, though all columns have a basically identical estimate, we take as a reference point the most robust 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 6.4 percent, as compared to other firms without ex-ante lending relationships with committed banks.[16] Notably, the described economic effect does not depend substantially on controls and fixed effects. Indeed, the magnitudes of the coefficients vary across columns in a tight [6.4, 8.6] percent interval.

Next, in Table 4, we 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, under our hypothesis, 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. Our results suggest that the decrease in total debt is entirely driven by bank debt, that is, a consequence of the direct channel, in which banks are the main force of debt adjustment. We discuss these results below in detail.

Since we can only dissect the fraction of debt financed by banks 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 4 for the larger sample of NFCs. In column 2, we estimate the same most robust version of equation (2) with bank debt as the dependent variable. Relative to unconnected firms, connected firms experience a reduction in bank debt if their scope 1 emissions are relatively larger. From an economic perspective, the decline amounts to 12.2 percent as a

[16] As we discussed in Section 2, the cross-sectional variation in the level of scope 1 is extremely high, and therefore, small variations of scope 1 (e.g., 1%) are not representative of the cross-section heterogeneity between brown versus green firms (the question in our paper). For example, in the cross-section of firms, the coefficient of variation with the median is around 50 and the firm in the 75th percentile of the empirical distribution has 13 times higher pollution than the one in the 25th percentile.

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.

4.2. Firm-level Debt: Robustness and Further Tests

We provide further robustness to our difference-in-differences model. 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, see right-hand side of the figure, we observe no significant impact of scope 1 emissions on credit, neither before, nor after 2015Q2.

In another test, we examine the differences between treated and control group based on a host of observables. We present the results from the balance test in Appendix, Table A2. Our results indicate no significant differences across the two samples across observables except for firm total assets. Firms that are part of the treatment group are on average larger than those of the control group. After controlling for size, firms are not different (statistically or based on normalized differences) between treated and control groups across carbon emissions (log scope 1), brownest firms (top 20% on scope 1), being in the oil or gas sector (which had a negative shock in 2014-16), sales growth, debt, risk, and leverage.

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.[17] 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

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

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).[18] 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.

In the Appendix, Table A3, we also check whether our results hold using different proxies for firms' connections to committed banks. Our baseline findings, reported in column 1, 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 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

[18] The idea is that the controls in column 5 when they are not controlled for in column 1, they are in the error term. As the estimated coefficient of postf,t*scope 1 does not change from column 1 to 5, this suggests that the unobserved covariance between the controls (firm observables and fixed effects) and our main right-hand-side variable are uncorrelated. Further, this lack of correlation also suggests that firm fundamentals (demand side) are orthogonal to our main results, and hence effects likely stem from credit supply. See below our results on prices (not just volumes) and on loan level data with firm-time fixed effects, which also support a credit supply mechanism for the results.

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 (e.g., Bolton et al. 2016), being connected to them becomes binding if committed lead arrangers have a sufficient weight in a firm's loan portfolio.

In the Appendix, Table A4, we analyze other measures of emissions. In column 1, we take the log level of scope 1, our benchmark model 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. The distinction in results between the two types of emissions is consistent with the fact that scope 1 emissions are easier to track and attribute to specific firm actions and hence, creditors find it easier to screen on such metrics. In turn, the results for scope 1 emission intensity are very similar to those based on levels of emissions.

In Table 5, Panel A, we control for industry-time fixed effects, either 1-digit or 3-digit SIC codes, as well as region-time fixed effects. Column 1 shows the benchmark result from Table 3, column 2 includes sector-time fixed effects, column 3 (3-digit) industry-time fixed effects,[19] and column 4 region-time fixed effects.[20] Results in columns 2 and 3 are statistically and economically significant. However, we observe a reduction of one-third in the estimated coefficient, which implies that the credit reallocation from brown to green is partly across industries and partly within the same industry in the same period.

In our subsequent tests, we shed more light on the underlying economic mechanism driving bank financing decisions. We consider two possible hypotheses. First, risk-averse banks cut credit to high-

[19] These industry-time fixed effects also control for time-varying shocks to some industries, such as the oil and gas industry. Our results are nevertheless robust to excluding some key industries, such as the oil and gas industry, which also suffered a negative shock in 2014-16. See Table A7.
[20] In our tests, regions largely correspond to continents. In the firm-level sample, we do not have enough variation in the data across countries in the same period. However, in loan-level sample, we can control for firm-time fixed effects, which allows us to absorb country or even a smaller location-time-fixed effects.

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 preferences for green versus brown assets. 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.[21] 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 5 of Table 4, 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 a one-standard-deviation 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 5.1 percent (relative to uncommitted firms), whereas the overall effect without controlling for firm risk is 6.4 percent.

In Table 5, Panel B, we study relative changes in debt maturity choices. If bank behavior was an outcome of *preferences* for green versus brown, one should expect loan maturity changes to be insignificant

[21] 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.

given that financial risk via climate risk (physical or transition) is mostly related to medium and long-term events. On the other hand, if the climate risk drove such maturity choices, we would expect their shortening since stranded asset risk is likely medium or long-term in nature. Columns 1 to 4 analyze log maturity and columns 5 to 8 analyze short-term loans (lower than the median). Our results do not indicate any significant change in maturity choices, the result that is more consistent with the preference hypothesis.

4.3. Loan-level Estimates

In this section, we report the results based on the loan-level sample. In Table 6, we analyze the interaction between the post and commitment indicators and firm scope 1 emissions. In all columns, we control for firm-year-quarter fixed effects, which proxy for firm-level time-varying unobserved shocks, including demand. This test is especially important to establish whether the credit adjustment is supply driven.[22] In other words, we can analyze lending from committed vs. non-committed banks to the same firm at the same time.

We analyze both the extensive and intensive margins of lending. 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. This result further supports the preference story along the lines of the divestment channel.

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 the combined loan margins by 8 % 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

[22] As the estimated coefficient increases in absolute value with controls (see column 4 vs. column 1), the Oster (2019) test also implies a significant lower bound.

4% of the standard deviation.

These results are robust. In Table 6, in addition to firm-time fixed effects, we control for bank observables or bank fixed effects, or firm-level controls interacted with bank commitments, and in Appendix, Table A5, we control for bank-time fixed effects or for loan variables such as bank as prior lead arranger or relationship length. Finally, we also find similar results using OLS with log values or using a Poisson model.

Regarding the robust results with bank-year-quarter fixed effects, the estimated coefficient is very similar to the regression without these fixed effects, and results hence suggest that there is reallocation of credit from committed banks from brown to green firms, as we control exhaustively for bank time-varying observed and unobserved variation, including total bank lending. That is, controlling for overall bank-level lending, we find that committed banks cut (increase) credit to the same at the same time if this firm is brown (green).

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. Results are shown in Table 7. A one-standard-deviation in scope 1 implies an increase in debt interest expenses by 2% of the mean or 4% of the standard deviation of expenses. The pricing effects, admittedly, are of smaller economic significance than the volume effects. This is not entirely surprising given that banks commit to greening out their loan portfolios, which essentially means cutting loans to issuers with higher carbon footprint and not necessarily just increasing prices while continue lending to them.

Overall, the results on the lending front suggest that committed banks do impose restrictions on polluting firms and reallocate funding towards greener firms, and that other lending options, both from uncommitted banks and debt markets, are not perfect substitutes for the affected firms.

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 question of our interest is whether such changes trigger any financial and real adjustments by the affected firms. Our empirical tests are guided by the theoretical literature on corporate finance decisions of firms facing shocks to real and financial flexibility (e.g., Bolton, Wang, and Yang, 2019). In particular, the model of Bolton et al. 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 their liquid assets reserves as precautionary motives.

We begin by investigating empirical effects on firm deleveraging. We report the results in Table 8. For ease of comparison, in columns 1 and 2, we repeat the analysis using bank debt and total debt as dependent variables. 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 significant decrease in leverage. The magnitude of the adjustment is, nonetheless, quite 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 60 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 to the same variation in scope 1 emissions (6.4 percent).

This result motivates our investigation of total assets as a separate dependent variable. We find that bank commitment is associated with a significant shrinkage 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.[23] When we decompose firm assets into

[23] A back of the envelope calculation suggests that the overall decline in leverage is roughly in line with the described magnitudes of the adjustment in the numerator (total debt) and denominator (total assets). Note, in fact, that, as for any ratio, we can write the first derivative of leverage with respect to *log-S1*$_f$ as the first derivative of the numerator

their equity portion, we do not observe any significant variation in firm equity associated with bank commitment, as reported in column 5. This result implies that firms do not substitute debt finance with equity funding perhaps, because equity finance is also relatively more expensive, consistent with evidence presented in Bolton and Kacperczyk (2021ab). 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 (log) *CAPEX*. In column 6, we observe a significant cut in firm investments. Connected firms with a one-standard-deviation higher scope 1 emissions reduce their *CAPEX* by 4.3 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 imply that tightened credit standards reduce the ability of high-emission firms to finance investments needed to improve their green technology.

Next, we study the effect of financing constraints on the accumulation of internal liquid assets, consistent with the cash hoarding hypothesis. We define liquid assets as the ratio of cash plus short-term investments and total assets, *LIQAT*. We show the results using this variable as dependent variable in column 7. We find a positive and statistically significant effect of bank commitments on liquid assets: Companies with high emissions exposed to committed banks subsequently increase their 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, firms with high emissions connected to committed banks subsequently realize higher ROAs. This result is consistent with the selection mechanism by which these firms, facing tighter credit constraints, abandon projects with lower profitability thereby increasing the average profitability of the remaining projects. Whether these projects are also projects with higher

(debt) minus the first derivative of the denominator (assets), multiplied by leverage itself. This corresponds to (-0.064 + 0.02) *leverage. For a firm with average leverage close to 30%, this translates in a 40-bps decline in leverage.

carbon footprint is the question we ask in the next section.

Overall, the results in this section indicate that the increased costs in external finance due to bank commitments affect subsequent borrowers' decisions. They reduce their debt, leverage, and investments, and increase their internal liquid resources. Results suggest that they also cut projects with the lowest profit margins.

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 could be that banks either cut lending to brown companies, which makes the brown firms scale down their assets, or they provide lending to brown firms which is then used as investment to improve the quality of brown assets. The two channels could be further enhanced by banks' monitoring. Our results so far suggest that the possible channel at play could be credit reduction. In this section, we examine whether the assets of brown companies indeed become greener as a result.

To evaluate this mechanism, we consider a host of regression models in which the dependent variables measure firms' environmental performance along various dimensions. We present the initial findings from this analysis in Table 9. As a first test, we examine whether connected firms reduce their scope 1 emissions. Our dependent variable is one-year-ahead scope 1 emissions measured on an annual basis. While the results suggest that the average connected firm reduces its scope 1 emissions by a significant 35 percent, 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), or whether they at least express their willingness to commit to future emission reduction, using again SBTi commitments as a relevant proxy (column 6). Again, we do not find any statistically significant incidence that emissions change in the longer horizon or that firms change the intensity of their commitment efforts. Therefore, despite firm-level real and financial effects associated with bank commitments for browner firms, we do not find any reduction in carbon emissions, which represent hard data (and choice).

Next, we consider a broadly defined ESG score as a dependent variable. The results in column 7 also show no relevant treatment effect, that is, connected firms with higher emissions do not seem to improve their ESG metrics. However, when we look specifically at the *E* component of the ESG score, which tracks environmental performance at the firm level, in column 8, we find some statistical differences. Connected firms with a one-standard-deviation higher scope 1 emissions improve their *E*-scores by roughly 10 basis points (as compared to firms with similar levels of emissions but without connections to committed banks). Still, the result is relatively small economically, given that the *E*-score varies between 0 and 10. In contrast, we do not observe any significant adjustment in environmental expenditures, neither when they are measured in logs (column 5), not when they are scaled by total assets (column 6). This variable, however, is available for only a very small subset of firms and hence our results here should be interpreted with caution. In column 7, we further study whether affected firms increase their usage of renewable energy. We find no significant result.

Given that after bank commitments, firms previously borrowing from these banks have lower total assets, but their carbon emissions do not change, if anything, affected firms may be even divesting green assets. At the same time, there could be some adjustments that may not be captured in our next year's scope 1 emission measure. For example, these firms could reduce (future) medium-term carbon emissions by increasing intangible assets, such as R&D in green technologies, the object that is not captured by *CAPEX*. In addition, it may take years to reduce carbon emissions for a brown firm. Nonetheless, we find no significant difference in SBTi NFC commitments to future reduction of carbon emissions for non-financial firms depending on whether they previously borrow or not from committed banks. All in all, our evidence points to no adjustments in hard data related to carbon emissions by the more affected firms.

As a final step of our analysis, we delve into 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. Interestingly, only the *E*-factor displays a significant change (improvement) for affected firms.

In the subsequent tests, we use different subcomponents of the *E-score*, defined by MSCI, as our left-hand-side variable. We do not find any improvement for affected firms in terms of their climate change mitigation efforts (column 5), waste reduction through a revision of product packaging policies (column 7), or carbon emissions (column 9). If anything, firms also perform worse in terms of their usage of natural resources (column 6).

The only small improvement observed in the *E*-factor results from a mixed improvement in the awareness of affected firms about environmental future opportunities (e.g., related to clean technology). Whether this effect reflects a changed corporate perspective on environmental problem or is a manifestation of greenwashing is difficult to confirm using our data. However, given that the there is no change in hard environmental data and only an improvement in future opportunities (via one subcomponent of ESG), our evidence is more consistent with greenwashing by affected firms. Combined with the significant reduction in bank debt, our results suggest that the latter may be a more likely explanation of firm policies, which the banks in fact do not find credible.[24]

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. It is conceivable that the effects may be more pronounced at the tail of the emissions' distribution. In this section, we examine whether the real effects we document exhibit any nonlinearities with respect to carbon emissions. Formally, we split firms into quintiles of the distribution of ex-ante scope 1 emissions and

[24] We do not find any significant effects related to firms' commitments to future emissions reductions. The results are reported in the Appendix, Table A6.

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 that, in relative terms, firms in quintile 1 (with the lowest emissions) experience an increase of 15% in total debt, compared to firms in quintile 5 (with the highest emissions). The results in columns 2 and 3 further indicate that this effect can be entirely explained by the adjustment in 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 a staggering 50%. Effects are mild for the remaining firms.

Further, like for the debt effects, we also find nonlinearities in *CAPEX* associated with bank commitments, with 17.8% higher firm investment levels for the greenest as compared to other firms. Finally, we find no significant evidence in carbon emissions following bank commitments even though the coefficient of $Post_{f,t}$ displays the negative sign consistent with the firms reducing their emissions.

4.7. The Effects on Bank Operations

Our results so far show the various consequences of bank commitments for NFCs. In this section, we study the implications of such decisions on banks themselves. Even though bank commitments are a choice for banks, looking at the impact on banks is a useful way to assess the costs-benefits tradeoffs that banks face when making their pledges.

In our analysis, we first 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 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 following a bank commitment, its portfolio exhibits lower carbon footprint. 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.

5. Conclusions

One of the most relevant questions in the current debate on climate policies is whether the financial sector can provide discipline to spur improvement in environmental performance of the corporate sector and whether such pressure in fact leads to material reductions in emissions. We analyze this problem in the context of the banking sector. We study this question using global data for the period of 2013-2018 and bank commitments as a form of changes in bank attitudes to green finance, which in turn implies shocks to firms with previous (over 2000-2012) credit from these banks.

We find that firms with higher scope 1 emission levels previously borrowing from banks making commitments subsequently receive less total bank credit. Effects are driven entirely by bank debt and are insignificant before the bank commitments. Not only do firms that previously borrowed from committing (versus other) banks are not different in levels of emissions (brown vs. green firms) or other fundamentals such as different risk or leverage, but results suggest that effects are also not driven by selection on unobservables. The economic mechanism at work is bank credit supply, and results are consistent with bank preferences for green rather than differential response to an increased firm risk. Moreover, the reduction in bank lending to brown firms triggers the reduction in these firms' total debt, leverage, total assets, and real investments. The effects are non-linear, with a strong increase (cut) in bank lending and investments for green (brown) firms, and mild effects for firms in between. Crucially, despite the associated real and financial effects, we find *no* improvement in hard firm-level environmental scores for brown firms – including subsequent reduction in carbon emissions or firm commitments to future (medium-term) reductions in carbon emissions– but only evidence consistent with firms' greenwashing.

Overall, the results suggest that banks affect carbon emissions via credit reallocation (from brown to green firms) rather than via providing loans to brown firms for the investment necessary to reduce carbon emissions.

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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 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%.

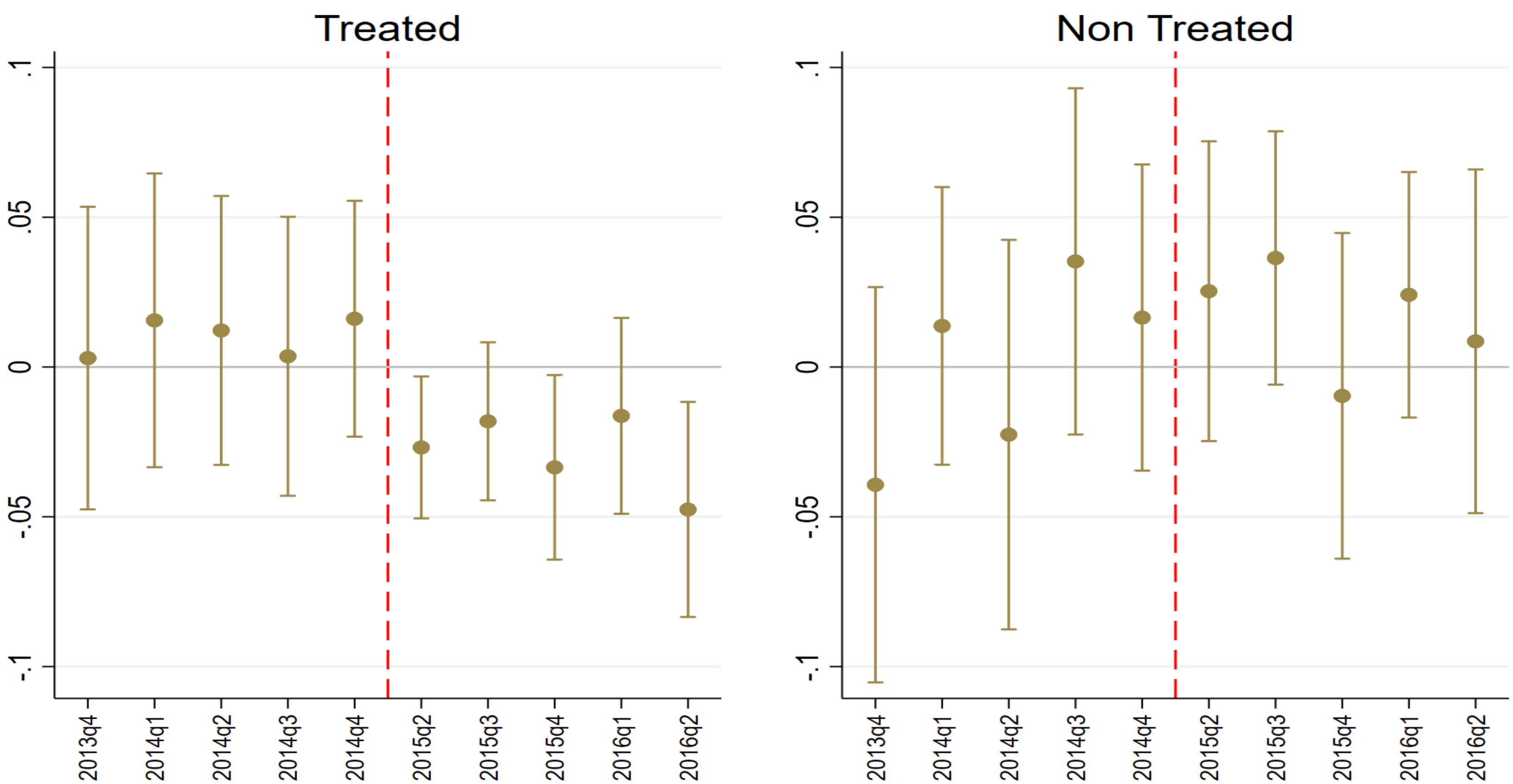

Table 1: Predicting Bank Commitments

The dependent variable is $Committed_{b,t}$. Climate risk index (*CRI*) is the country-level measure of climate risk. Institutional ownership (*IO*) is the percentage level of bank ownership that is held by institutional investors. Ownership concentration (*TOP 5*) is defined as a fraction of bank shares that is held by five largest institutional owners. *ESS* measures the positive slant of media coverage. *LOYALTY* measures the loyalty of the bank clients. Board size (*BOARD*) is the number of board members sitting on a bank's board. The sample period is 2015-2018. Standard errors are double clustered at the bank and year level. ***p<.01, **p<.05, *p<.1.

DEP. VAR.: $Committed_{b,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CRI*100	0.060						0.052					
	(0.039)						(0.062)					
IO		0.275*						0.270				
		(0.152)						(0.249)				
TOP5			0.500						0.478			
			(0.341)						(0.423)			
ESS*100				-0.129						-0.035		
				(0.084)						(0.073)		
LOYALTY					0.393*						2.943**	
					(0.208)						(1.187)	
BOARD						0.028						0.084*
						(0.046)						(0.044)
Constant	0.008	-0.008	0.003	0.093*	-0.223	0.048*	0.012	-0.007	0.004	0.041	-2.076*	0.023
	(0.016)	(0.024)	(0.022)	(0.045)	(0.151)	(0.021)	(0.027)	(0.038)	(0.026)	(0.038)	(0.859)	(0.013)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Bank FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	592	614	614	436	358	358	588	610	610	474	391	391
R-squared	0.046	0.244	0.229	0.255	0.275	0.249	0.538	0.538	0.539	0.579	0.543	0.544

Table 2: Summary Statistics

The sample period is 2013-2018. Ex ante variables are averaged over 2013-14.

VARIABLES		(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Firm-Level Variables							
Log-S1$_{ft}$	Log (Scope-1 Emissions tonnes)	8,691	11.78	2.538	10.03	11.55	13.42
Log-S1$_{f}$ (ex-ante)	Log-S1 (ex-ante)	2,112	11.78	2.538	10.04	11.54	13.39
Log-S1$_{f}$	Log-S1 (ex-ante, demeaned)	2,112	0	2.538	-1.737	-0.238	1.608
Treat$_{f}$	Firm indicator if a firm ever has a lender that commits	41,450	0.769	0.421	1	1	1
Post$_{f,t}$	Time indicator after a firm has at least 1 prior lender committing	41,450	0.383	0.486	0	0	1
Lead Post$_{f,t}$	Time indicator after a firm has at least one bank who was a prior lead commit	41,450	0.266	0.442	0	0	1
% Committed$_{f}$	% of a firm's prior lenders who eventually commit	41,450	0.150	0.178	0	0.107	0.200
Lead Committed$_{f}$	Firm indicator if a firm ever has a prior lead lender that commits	41,450	0.562	0.496	0	1	1
% Lead Committed$_{f}$	% of a firm's prior lead lenders who eventually commit	41,450	0.128	0.184	0	0.0625	0.194
% Post$_{f,t}$	% of a firm's prior lenders who eventually commit, 0 before first commitment	41,450	0.0785	0.148	0	0	0.118
% Lead Post$_{f,t}$	% of a firm's prior leads who eventually commit, 0 before first commitment	41,450	0.0638	0.145	0	0	0.0339
Total Debt	Log(Total Debt)	41,450	7.152	1.543	6.230	7.369	8.387
Bank Debt	Log(Bank Debt +1)	32,844	5.367	2.468	4.581	6.041	7.232
Non-Bank Debt	Log(Non-Bank Debt +1)	32,844	5.503	2.885	4.047	6.488	7.818
Leverage	Total Debt / Total Assets	41,450	0.304	0.155	0.202	0.307	0.375
Assets	Log(Total Assets)	41,450	8.534	1.169	7.747	8.623	9.598
LIQAT	Liquid Assets/Assets	41,444	0.0970	0.0876	0.0382	0.0842	0.1165
Equity	Log(Total Equity)	40,318	7.471	1.157	6.757	7.600	8.496
ROA	Return on Assets	38,311	0.0088	0.0249	0.0028	0.0099	0.0184
Risk	Leverage * Prior 12 month equity volatility	37,641	10.55	8.606	5.218	7.845	12.23
Revenue growth (ex-ante)	% growth in revenue	2,112	0.0540	0.233	-0.0496	0.0202	0.0905
Assets (ex-ante)	Log(Total Assets)	2,112	8.384	1.205	7.582	8.455	9.444
Capital Expenditures	Log(Capital Expenditure)	38,120	3.723	1.550	2.762	3.932	5.148
Interest Expense	Interest Expense / Total Debt, winsorized 2.5% both tails	36,951	0.0123	0.00775	0.00833	0.0106	0.0141
ESG Score	MSCI Environmental Social and Governance score	31,687	4.730	1.163	4	4.700	5.500
Env Score	MSCI Environmental sub-score	31,687	5.149	2.209	3.500	4.900	6.500
Soc Score	MSCI Social sub-score	31,687	4.482	1.758	3.400	4.500	5.600
Gov Score	MSCI Governance sub-score	31,685	5.585	2.085	4.100	5.500	7

Climate Score	MSCI Climate Change sub-sub-score	29,269	6.411	2.881	4.400	6.700	9
Natural Resource Score	MSCI Natural Resource sub-sub-score	24,623	4.992	2.486	3.300	4.700	6.500
Waste Mgmt Score	MSCI Waste Management sub-sub-score	24,016	5.498	2.577	3.600	5.500	7.600
Env Opp Score	MSCI Environmental Opportunity sub-sub-score	13,420	4.579	1.561	3.400	4.400	5.700
Carbon Score	MSCI Carbon sub-sub-score	26,614	6.929	2.706	5.300	7.200	9.500
Env Exp_{t+1}	Next year Log(Environmental Expenditures + 1)	1,962	4.082	2.954	1.902	3.621	5.720
Renewable Use	Indicator if a firm uses renewables	35,112	0.506	0.500	0	1	1
Firm Commitments	Time indicator if a firm commits	41,450	0.00914	0.0952	0	0	0
Maturity	Log(Maturity)	945	3.726	.7156	3.583	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)	7,170	3.951	1.512	3.266	4.070	4.823
$ Extensive + Intensive	Loan Amount (USD millions)	60,907	10.85	43.64	0	0	0
$Post_{b,t}$	Time indicator after a lender commits	60,907	0.0320	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)	44,346	11.61	0.700	11.57	11.96	11.96
Bank Tier 1 (ex ante)	Bank tier 1 capital ratio	35,436	13.28	3.134	11.55	12.92	13.71
Bank Prior Leader	Indicator if the lender was a prior lead lender to the firm	60,907	0.352	0.477	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 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-$S1_f$	-0.0278*	-0.0323**	-0.0313**	-0.0255***	-0.0240***
	(0.0167)	(0.0129)	(0.0130)	(0.0082)	(0.0082)
$Post_{f,t}$	0.3131***	0.0945	0.0593	0.1764	0.1180
	(0.0375)	(0.2774)	(0.2786)	(0.2220)	(0.2227)
$Post_t$ * Log-$S1_f$	-0.0221*	0.0009	0.0001	-0.0033	-0.0049
	(0.0125)	(0.0108)	(0.0108)	(0.0081)	(0.0081)
$Treat_f$ * Log-$S1_f$	-0.0529**	-0.0165	-0.0169		
	(0.0260)	(0.0188)	(0.0189)		
$Post_t$	-0.0392	0.7298***		0.4459**	
	(0.0278)	(0.2570)		(0.1915)	
$Treat_f$	0.3551***	-1.0275**	-1.0189**		
	(0.0619)	(0.4105)	(0.4103)		
Log-$S1_f$	0.3629***	0.0515***	0.0519***		
	(0.0216)	(0.0165)	(0.0165)		
Observations	41,450	41,450	41,450	41,450	41,450
R-squared	0.3066	0.7044	0.7055	0.9042	0.9053
Econ effect 1sd	-.074	-.086	-.083	-.068	-.064
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 $Post_t$. 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-$S1_f$	-0.0215***	-0.0456*	-0.0050
	(0.0073)	(0.0237)	(0.0218)
$Post_{f,t}$	0.1850	-0.1558	0.2067
	(0.2392)	(0.4757)	(0.4933)
$Post_t$ * Log-$S1_f$	-0.0074	-0.0046	-0.0120
	(0.0066)	(0.0187)	(0.0200)
Observations	32,828	32,828	32,828
R-squared	0.9127	0.7456	0.8014
Econ effect 1sd	-.057	-.122	-.013
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: Robustness

The dependent variable in Panel A is *Total Debt*. In each column we introduce a new control to check for robustness. Column (1) is the baseline result. Column (2) introduces sector-year fixed effects. Column (3) uses the more granular 3-digit industry-year fixed effects. Column (4) uses region-time fixed effects. Column (5) includes firm risk, defined as stock volatility times leverage. 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-$S1_f$	-0.0240***	-0.0164*	-0.0166*	-0.0236***	-0.0191**
	(0.0082)	(0.0085)	(0.0086)	(0.0082)	(0.0076)
$Post_{f,t}$	0.1180	0.1217	0.0078	0.1403	0.2938
	(0.2227)	(0.2216)	(0.2177)	(0.2266)	(0.2025)
$Post_t$ * Log-$S1_f$	-0.0049	-0.0033	0.0129	-0.0008	-0.0014
	(0.0081)	(0.0089)	(0.0094)	(0.0082)	(0.0075)
$Risk_{ft}$					0.0476***
					(0.0045)
$Post_{f,t}$* $Risk_{ft}$					-0.0067***
					(0.0021)
$Post_t$ * $Risk_{ft}$					-0.0114***
					(0.0019)
$Treat_f$* $Risk_{ft}$					-0.0034
					(0.0052)
Observations	41,450	40,863	41,459	41,276	37,647
R-squared	0.9053	0.9056	0.9163	0.9067	0.9213
Econ effect 1sd	-.064	-.044	-.044	-.063	-.051
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	No	Yes	-	No	No
Industry3-Year FE	No	No	Yes	No	No
Region-Time FE	No	No	No	Yes	No

Panel B: Firm-Level Loan Maturity

The regression is estimated at the firm level on an unbalanced panel aggregated from syndicated loans. If a firm has multiple loans in a quarter, they are averaged. Columns (1)-(4) use log maturity as the dependent variable. Columns (5)-(8) use an indicator for if the maturity is below the median as the dependent variable. 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. 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	-0.0126	0.0020	-0.0031	-0.0057	-0.0090
	(0.0191)	(0.0217)	(0.0206)	(0.0335)	(0.0131)	(0.0148)	(0.0149)	(0.0230)
Observations	945	945	904	414	945	945	904	414
R-squared	0.0312	0.0759	0.1208	0.7248	0.0163	0.0326	0.0425	0.6587
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

This table shows how lender commitments to reducing emissions impacts their lending to firms differentially depending on the firm's level of emissions. The data is at the borrower-lender-year-quarter level. If a lender has previously participated in a loan to the firm, but does not in the current period, they are coded as zero lending for columns (1) to (4) and column (6). From columns (1) to (5) if a lender provides a loan to the firm, the value is the log of the credit volume plus one until column (4) and the log of the credit volume in column (5). Therefore, columns (1)-(4) examine the extensive and intensive margins of lending together, while column (5) only the intensive and column (6) only the extensive margin. Firm controls are interacted with bank commitment. Lower-level interactions are included but not shown. Standard errors are double clustered at the firm and bank level. ***p<.01, **p<.05, *p<.1.

VARIABLES\ MODEL	(1) Intensive+ Extensive	(2) Intensive + Extensive	(3) Intensive + Extensive	(4) Intensive + Extensive	(5) Intensive	(6) Extensive
$Post_{b,t}$* Log-$S1_f$	-0.0159*	-0.0302**	-0.0238*	-0.0308**	0.0337	-0.0055*
	(0.0091)	(0.0140)	(0.0132)	(0.0137)	(0.0220)	(0.0030)
Observations	60,907	60,907	35,189	60,907	6,964	60,907
R-squared	0.4085	0.4088	0.5130	0.4735	0.8933	0.4762
Econ effect 1sd	-.041	-.079	-.062	-.080	.088	-.014
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 $Post_t$. 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-$S1_f$	0.0001	0.0007**
	(0.0001)	(0.0003)
$Post_{f,t}$	-0.0009	0.0034
	(0.0018)	(0.0061)
$Post_t$ * Log-$S1_f$	0.0001	0.0001
	(0.0001)	(0.0001)
Observations	36,946	36,946
R-squared	0.5452	0.5460
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. 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.

VARIABLES	(1) Bank Debt	(2) Total Debt	(3) Leverage	(4) Assets	(5) Equity	(6) CAPEX	(7) LIQAT	(8) ROA
$Post_{f,t}$* Log-$S1_f$	-0.0456*	-0.0269***	-0.0024**	-0.0081**	0.0001	-0.0160**	0.0013**	0.0010***
	(0.0237)	(0.0087)	(0.0012)	(0.0040)	(0.0060)	(0.0080)	(0.0006)	(0.0080)
$Post_{f,t}$	-0.2232	0.0978	0.0317	0.1364	0.0965	-0.0511	0.0035	0.0015
	(0.4774)	(0.2223)	(0.0262)	(0.0863)	(0.1258)	(0.1759)	(0.0152)	(0.0052)
$Post_t$ * Log-$S1_f$	0.0003	-0.0057	-0.0002	-0.0077**	-0.0067	-0.0198**	-0.0198**	-0.0006***
	(0.0184)	(0.0085)	(0.0011)	(0.0035)	(0.0051)	(0.0079)	(0.0079)	(0.0002)
Observations	32,828	41,450	41,450	41,450	40,316	38,126	38,126	38,126
R-squared	0.7456	0.9054	0.8276	0.9722	0.9267	0.8896	0.8896	0.3446
Econ effect 1sd	-.138	-.068	-.006	-.02	0	-.043	.003	.002
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 $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1

VARIABLES	(1) Log-$S1_{t+1}$	(2) Log-S_{t+2}	(3) Log-$S1_{t+3}$	(4) Log-S1 $_{(t+1, t+2)}$	(5) Log-S1 $_{(t+1, t+3)}$	(6) Committed	(7) ESG Score	(8) Env Score	(9) Env Exp_{t+1}	(10) Env Exp_{t+1}/TA	(11) Renewable
$Post_{f,t}$* Log-$S1_f$	-0.0002	-0.0106	-0.0013	0.0017	-0.0047	-0.0003	0.0090	0.0362**	-0.0161	-0.0392	0.0005
	(0.0122)	(0.0121)	(0.0146)	(0.0132)	(0.0104)	(0.0012)	(0.0104)	(0.0184)	(0.0330)	(0.0962)	(0.00463)
$Post_{f,t}$	-0.3554*	-0.3452*	-0.2330	-0.3114**	-0.3134**	-0.0724***	-0.0316	0.4246	-0.0029	0.5622	0.0642
	(0.1998)	(0.1918)	(0.2412)	(0.1584)	(0.1490)	(0.0254)	(0.2106)	(0.4332)	(0.5998)	(1.1263)	(0.0836)
$Post_t$ * Log-$S1_f$	-0.0309***	-0.0013	-0.0073	-0.0258*	-0.0162*	-0.0021**	0.0442***	0.0140	-0.0374	-0.0942*	-0.0089**
	(0.0113)	(0.0116)	(0.0076)	(0.0137)	(0.0097)	(0.0010)	(0.0107)	(0.0168)	(0.0252)	(0.0567)	(0.0039)
Observations	8,638	6,882	5,157	6,843	5,096	41,450	31,668	31,668	1,911	1,911	35,112
R-squared	0.9699	0.9765	0.9813	0.9822	0.9914	0.3555	0.8455	0.8568	0.9670	0.7361	0.8421
Econ effect 1sd	-.001	-.028	-.004	.005	-.013	-.001	.024	.097	-.043	-.104	.001
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. 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 $Post_t$. Standard errors are clustered at the firm level. ***p<.01, **p<.05, *p<.1.

VARIABLES	(1) ESG	(2) Env	(3) Soc	(4) Gov	(5) Climate	(6) Natural Res	(7) Waste	(8) Env Ops.	(9) Carbon
$Post_{f,t}$* Log-$S1_f$	0.0090	0.0362**	0.0138	0.0074	0.0286	-0.0429*	-0.0105	0.0732***	-0.0102
	(0.0104)	(0.0184)	(0.0192)	(0.0242)	(0.0277)	(0.0252)	(0.0199)	(0.0220)	(0.0262)
$Post_{f,t}$	-0.0316	0.4246	-0.3034	-0.3941	0.4837	-0.3337	-0.7551	0.7134	0.7986
	(0.2106)	(0.4332)	(0.3571)	(0.4999)	(0.6441)	(0.5880)	(0.4982)	(0.5046)	(0.5963)
$Post_t$ * Log-$S1_f$	0.0442***	0.0140	-0.0331	-0.0399	-0.0273	-0.1304***	-0.1731***	0.0471**	-0.0512**
	(0.0107)	(0.0168)	(0.0202)	(0.0277)	(0.0249)	(0.0258)	(0.0203)	(0.0210)	(0.0248)
Observations	31,668	31,668	31,668	31,666	29,247	24,570	23,933	13,413	26,582
R-squared	0.8455	0.8568	0.7607	0.5967	0.8595	0.8008	0.8519	0.8027	0.8774
Econ effect 1sd	.024	.097	.037	.02	.076	-.114	-.028	.195	-.027
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 scope 1 emissions. Quintile 1 represents the firm observations with 20% lowest emission levels and Quintile 5 (omitted baselevel) represents the firm observations with 20% highest emission levels. 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) Total Debt	(2) Bank Debt	(3) Nonbank Debt	(4) CAPEX	(5) Log-S1
$Post_{f,t}$ * Quintile 1_f	0.1508**	0.5053**	0.0364	0.1782**	0.0168
	(0.0611)	(0.1972)	(0.1835)	(0.0696)	(0.0747)
$Post_{f,t}$ * Quintile 2_f	0.1946***	0.2277	0.2903*	0.0703	-0.0041
	(0.0549)	(0.1647)	(0.1593)	(0.0593)	(0.0716)
$Post_{f,t}$ * Quintile 3_f	0.1201**	0.0176	0.2145	0.0732	0.0281
	(0.0486)	(0.1651)	(0.1422)	(0.0557)	(0.0657)
$Post_{f,t}$ * Quintile 4_f	0.0148	-0.0887	0.2357	0.0146	0.0657
	(0.0455)	(0.1479)	(0.1501)	(0.0551)	(0.0577)
$Post_{f,t}$	-0.3239	-0.8954	0.0126	-0.4828**	-0.2562
	(0.2896)	(0.5572)	(0.6062)	(0.2430)	(0.1953)
Observations	32,838	32,838	32,838	30,351	32,838
R-squared	0.9140	0.7473	0.8024	0.8818	0.9708
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*). The main independent variable is $Committed_{b,t}$. The regression model is estimated using weighted least square with weights defined as the loans granted by a bank in a given year. Standard errors are clustered at the bank level. ***p<.01, **p<.05, *p<.1.

	(1)	(2)	(3)	(4)
VARIABLES	S1//#*Loans*	*S1/Loan Volume*	*WLogscope1*	*Wscope1int*
$Committed_{b,t}$	0.0309	-0.2841*	-0.0341	-35.8347**
	(0.1003)	(0.1640)	(0.1757)	(16.1799)
Observations	773	576	773	773
R-squared	0.6798	0.5550	0.6310	0.5336
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Appendix

Appendix 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. Left panel presents all the banks with commitments, while the right panel presents banks which can be merged with Compustat.

Committed Lenders in SBTi

1-Nov-15	Westpac Banking Corp	1-Apr-16	BNP Paribas SA
1-Apr-16	Societe Generale SA	1-Nov-18	Swedbank AB (publ)
1-Jul-18	Standard Chartered Bank Plc [SCB]	1-Jul-18	Daegu Bank Seoul
1-Oct-18	Royal Bank of Scotland Plc [RBS]	1-Dec-16	Fubon Financial Holding Co Ltd
1-Jun-15	Turkiye Is Bankasi AS [Isbank]	1-Apr-16	Mitsui Sumitomo Insurance Co Ltd
1-Nov-15	Bank of Australia	1-Jan-18	Sompo Japan Insurance Co Ltd
1-Jun-16	HSBC Banking Group	1-Jan-18	BBVA
1-Oct-16	Grupo Financiero Banorte	1-Apr-16	MetLife Inc
1-Apr-18	Commercial International Bank (Egypt) SAE	1-Sep-18	Yes Bank Ltd
1-Jul-19	Zurich Insurance Group AG	1-Mar-18	Tokio Marine & Nichido Fire Insurance Co Ltd
1-Jun-15	Banco Safra SA	1-May-18	Euler Hermes Kreditversicherungs AG
1-Jun-15	AXA Group SA	1-May-16	Credit Agricole CIB
1-Jun-15	ING Group	1-May-18	Raiffeisen Bank International AG [RBI]
1-Nov-15	Bancolombia	1-Oct-17	La Banque Postale SA

Committed Lenders in Compustat

1-Jan-18	BBVA
1-Nov-15	WESTPAC BANKING
1-Oct-18	ABN-AMRO HOLDINGS NV
1-Jun-16	HSBC HLDGS PLC
1-Apr-16	BNP PARIBAS
1-Jun-15	ING GROEP NV
1-Jul-18	STANDARD CHARTERED PLC
1-Apr-16	SOCIETE GENERALE GROUP
1-Nov-15	BANCOLOMBIA SA
1-Apr-18	COMMERCIAL INTL BK EGYPT SAE
1-Sep-18	YES BANK LTD

Appendix Table A2: Balancedness across Firms

The value displayed for t-tests and normalized differences are the differences in the means across the groups of firms with syndicated loans. Variables are predetermined and calculated as averages over 2013-2014. Variables are residualized against total assets (except total assets itself). Normalized differences are significant if the value is higher than 0.25 in absolute value (see Imbens and Wooldridge, 2009). ***p<.01, **p<.05, *p<.1.

	Not Committed		Committed		t-test Difference	Normalized difference
Variable	**N**	**Mean/SE**	**N**	**Mean/SE**	**(1)-(2)**	**(1)-(2)**
Log-S1	632	0.102 [0.078]	1481	-0.043 [0.056]	0.145	0.069
Total Debt	607	-0.022 [0.037]	1459	0.009 [0.022]	-0.031	-0.036
Total Assets	632	7.955 [0.050]	1481	8.566 [0.030]	-0.612***	-0.507
Revenue Growth	632	-0.002 [0.013]	1481	0.001 [0.005]	-0.003	-0.014
Leverage	617	-0.006 [0.006]	1467	0.002 [0.004]	-0.008	-0.054
Risk	564	0.383 [0.327]	1372	-0.157 [0.201]	0.540	0.072
Oil & Gas	632	-0.010 [0.008]	1481	0.004 [0.006]	-0.015	-0.068
Brownest	632	-0.006 [0.012]	1481	0.003 [0.010]	-0.009	-0.025

Appendix Table A3: 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 a 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$_f$	-0.0240***	-0.0937***	-0.0102	-0.0718**
	(0.0082)	(0.0331)	(0.0091)	(0.0328)
$Post_{f,t}$	0.1180	-1.3051**	0.2168	-0.8408
	(0.2227)	(0.5379)	(0.2545)	(0.5486)
$Post_t$ * Log-S1$_f$	-0.0049	-0.0099	-0.0154**	-0.0139**
	(0.0081)	(0.0071)	(0.0073)	(0.0066)
Observations	41,450	41,450	41,450	41,450
R-squared	0.9053	0.9052	0.9052	0.9052
Econ effect 1sd	-.064	-.044	-.027	-.034
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Appendix Table A4: Other Emission Measures (Scope 1, 2, and 3)

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		
$Post_{f,t}$* $Trucost_f$	-0.0269***	0.0042	0.0061	-0.0001***
	(0.0087)	(0.0123)	(0.0159)	(0.0001)
$Post_{f,t}$	0.0978	0.4360*	0.4457*	0.3485*
	(0.2223)	(0.2327)	(0.2529)	(0.2072)
$Post_t$ * $Trucost_f$	-0.0057	0.0046	-0.0164	-0.0001
	(0.0085)	(0.0106)	(0.0142)	(0.0001)
Observations	41,450	41,450	41,450	41,450
R-squared	0.9054	0.9051	0.9051	0.9052
Trucost	Log-S1	Log-S2	Log-S3	S1 Intensity
Econ effect 1sd	-.068	.008	.01	-.036
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Appendix Table A5: 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-$S1_f$	-0.0285*	-0.0340*	-0.0338**	-0.0269*
	(0.0145)	(0.0202)	(0.0138)	(0.0141)
Observations	58,695	15,733	60,907	60,907
R-squared	0.5094		0.4813	0.4783
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

Appendix Table A6: 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$_f$*	0.0774*	0.1625***	0.1491**	-0.1649	-0.0719	0.0599	0.0696	-0.0019	-0.0495	-0.0594	-0.0756	0.0132
NFC Committed$_{ft}$	(0.0465)	(0.0589)	(0.072960)	(0.1128)	(0.0852)	(0.0965)	(0.1141)	(0.0620)	(0.0707)	(0.0444)	(0.2758)	(0.0146)
$Post_{f,t}$ * Log-S1$_f$	0.0055	0.0304	0.0119	0.0144	0.0244	-0.0478*	-0.0196	0.0711***	-0.0230	-0.0059	-0.0061	0.0004
	(0.0110)	(0.0195)	(0.0204)	(0.0256)	(0.0294)	(0.0271)	(0.0215)	(0.0241)	(0.0280)	(0.0115)	(0.0292)	(0.0048)
$Post_{f,t}$ * Log-S1$_f$ *	0.0254	0.0005	0.0142	0.0329	-0.0001	0.2534	0.0664	-0.1449	-0.1922	0.0883	0.9794	-0.0366
NFC Committed$_{ft}$	(0.1192)	(0.1978)	(0.2113)	(0.2946)	(0.2373)	(0.3313)	(0.2257)	(0.1794)	(0.1496)	(0.1021)	(0.9232)	(0.0373)
$Post_t$ * Log-S1$_f$	0.0448***	0.0109	-0.0282	-0.0435	-0.0280	-0.1448***	-0.1858***	0.0407*	-0.0587**	-0.0262**	-0.0406	-0.0107**
	(0.0115)	(0.0182)	(0.0214)	(0.0297)	(0.0268)	(0.0278)	(0.0224)	(0.0228)	(0.0269)	(0.0104)	(0.0272)	(0.0043)
$Post_t$ * NFC	-0.0044	-0.0822	0.0799	-0.2839	0.0715	0.0010	0.0107	0.0049	-0.1996	0.0353	-0.4240*	-0.0132
Committed$_{ft}$	(0.1070)	(0.1662)	(0.1682)	(0.3513)	(0.2060)	(0.3051)	(0.2277)	(0.1816)	(0.1226)	(0.0664)	(0.2473)	(0.0271)
Observations	31,668	31,668	31,668	31,666	29,247	24,570	23,933	13,413	26,582	8,633	1,911	35,112
R-squared	0.8455	0.8569	0.7609	0.5972	0.8595	0.8013	0.8522	0.8017	0.8777	0.9703	0.9673	0.8422
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

Table A7: 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-$S1_f$	-0.0407*	-0.0207**	-0.0019*	-0.0049	-0.0000	-0.0139*	0.0013**	0.0008***
	(0.0239)	(0.0083)	(0.0011)	(0.0037)	(0.0055)	(0.0080)	(0.0006)	(0.0002)
$Post_{f,t}$	-0.0831	0.1048	0.0309	0.1238	0.0872	-0.0644	0.0029	0.0033
	(0.4745)	(0.2252)	(0.0259)	(0.0818)	(0.1242)	(0.1720)	(0.0147)	(0.0048)
$Post_t$ * Log-$S1_f$	-0.0023	-0.0043	-0.0008	-0.0057*	-0.0040	-0.0141*	0.0002	-0.0003
Observations	31,000	39,277	39,277	39,277	38,220	35,982	39,256	36,149
R-squared	0.7560	0.9064	0.8373	0.9747	0.9297	0.8965	0.8258	0.3604
Econ effect 1sd	-.108	-.055	-.005	-.013	0	-.037	.003	.002
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

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