Financed Emissions*

Mustafa Emin[1], Nishad Kapadia[2], Robert Prilmeier[2], William Waller[2]

Abstract

We examine targets set by banks for the emissions of their lending portfolio in specific industries. We characterize the distribution of these "financed emissions" targets across banks and industries. We find substantial heterogeneity in the stringency of targets. While the mean target is ambitious, implying a 8.6% annualized reduction in emissions in excess of past industry trends, about 25% of targets imply reductions that are less than past trends. We also find heterogeneous effects of bank targets on real economic activity. We clusters banks into three groups: greenwashers, divestors, and transformative investors. Greenwasher banks do not reduce lending to target industries and firms that borrow from them do not reduce emissions. Divestors reduce lending to target industries. 'Transformative investor' banks increase lending to target industries, and firms that borrow from these banks increase investment and reduce emissions.

Keywords: lending, emissions, bank targets
JEL Classification: G21, G30, Q50

*This version: July 31, 2024
First draft: February 28, 2024

This is a preliminary draft. Please do not cite or circulate without the permission of the authors.

[1]University of Alabama
[2]Tulane University – A.B. Freeman School of Business

1. Introduction

The overarching goal of the Paris Climate Agreement is to limit "the increase in the global average temperature to well below 2°C above pre-industrial levels." To achieve this ambitious goal, the United Nations estimates that emissions must reach "net zero" by 2050. Rather than mandating compulsory emissions reductions as in the Kyoto agreement, the Paris agreement relies on voluntary commitments to achieve its target. Following the agreement, more than 140 countries and 9,000 companies have made pledges to achieve net zero emissions by 2050.[1]. In this paper, we examine a set of voluntary emissions targets that have the potential to make a large impact: targets set by financial institutions for the aggregate emissions of their lending portfolios, also known as 'financed emissions'.

Why do banks set voluntary public targets? A public target necessarily curtails a banks lending opportunity set and thus could be value-destroying if it inhibits the bank from making profitable loans. Over the past few years, as climate concerns have grown, a range of constituencies including regulators, environmental activists, shareholders, and customers are pressing banks to act on global warming.[2] One possibility is that these targets are 'cheap talk' or attempts at greenwashing: lofty promises intended to dampen these external pressures but resulting in minimal real changes. Another possibility is that banks are sincere because they believe that reducing exposure to emitting firms mitigates physical and transition risks associated with climate change and also strengthens their brand.

Two recent papers investigate this question and arrive at conflicting answers. Kacperczyk and

[1] Source: https://racetozero.unfccc.int/join-the-race/whos-in

[2] For example, Dursun-de Neef and Ongena (2023) find that bank depositors shift deposits away from banks that finance fossil fuel companies when they experience local temperature shocks

Peydró (2022) find that banks that set emissions targets under Science Based Targets Inititiative (SBTi) reduce their lending to high emitting firms. On the other hand, Sastry, Verner, and Ibanez (2024) find that emissions targets make no difference to bank lending. However, neither paper collects data on exactly what targets are set, and hence cannot examine the diversity in bank targets and outcomes. We hand-collect sector-wise targets of institutions that are among the 50 largest lenders in either the US or in the worldwide market in any year during the 2010–2022 period. This allows us to characterize the diversity in bank strategies in this space, and thereby provide a more nuanced answer to the question of whether emissions targets affect lending and real firm outcomes.

We first describe the financed emissions targets set by banks. We find that 45 of the 80 banks in this sample set an emissions target for their lending in at least one sector.[3] These targets cover a significant fraction of the banking sector's lending portfolio: by 2023 over 15% of new loans made by banks are to firms in industries in which banks have targets. When focusing on sectors with substantial greenhouse gas emissions, the coverage of targets is even larger. For example, about 80% of the total loan amount in the electricity, gas, and sanitary services sector (utilities) in 2023 are made by banks with targets in that sector.

Many banks that set targets are part of the 'Net-Zero Banking Alliance' and have committed achieving net zero emissions for their entire lending portfolio by 2050. However, because a target date of 2050 is beyond the horizon of most managers, banks typically set industry-specific targets that are closer in time. Some targets are set for as early as 2024, but most targets are for 2030. Foreign banks are more likely to set targets than US banks, and the banks that set targets tend to be larger than those without targets. Only about 18% of bank targets are reductions in the level

[3] Although there are 10 nonbanks in our set of lenders, none have set targets. Hence we refer to all sample institutions as banks.

of emissions ('absolute' targets); the remaining 82% are reductions in the intensity of emissions (e.g., metric tons of CO_2 per metric ton of steel produced). Finally, 88% of targets are for scope 1 emissions, 65% for scope 2, 38% for scope 3. Scope 3 emissions are more likely to be covered in industries such as auto manufacturing and oil and gas mining, in which large emissions occur downstream when the product is used rather than produced.

However, banks may set targets that reflect rather accelerate existing trends in industries. For example, emissions declined substantially from 2005 to 2022 in the US electricity generation sector due to the shift from coal to natural gas and renewables. A target that projects this current trend into the future may be redundant because it will likely be achieved even without the bank's intervention. In fact, a seemingly stringent absolute target that is nevertheless likely to be achieved because of industry trends may be an easy way for a bank to greenwash without affecting its lending business.

We therefore examine whether bank targets are ambitious relative to industry trends. When industry trends are removed with an exponentially weighted five-year moving average, the mean target is slightly reduced to a relative reduction of 8.6%. Although smaller, this reduction is considerable, implying a reduction of 48% over eight years. And yet, there remains substantial heterogeneity and skewness in targets. The median relative reduction is only 6.2%; about 25% of bank targets do not require greater reductions than those already occurring in the industry.

The heterogeneity in bank targets suggests that banks follow different strategies in this space. We therefore characterize bank strategies using two simple variables: targeted reductions relative to industry trends and whether banks reduce lending in targeted sectors. The reduction is measured relative to that bank's lending in the sector prior to the target and also to lending by all banks in the sector that year, and hence will not mechanically pick up banks that reduce lending in general or sectors that receive less financing as a whole. We run a cluster analysis on these two variables and find three distinct clusters. We call these clusters greenwashers, divestors, and transformative investors.

The greenwasher cluster contains banks whose targets are below industry trends and do not reduce lending in targeted industries. The divestor cluster contains banks with targets that are stricter than industry trends that also reduce lending in targeted industries. Transformative investors are banks with stringent targets that do not reduce lending, because the only way in which they can achieve strict targets while continuing to lend to firms in the targeted sector is if their borrowers transform their business to reduce emissions.

We perform several tests that validate these labels. We find that although investors increase the number of deals in which they participate after setting targets, the increase is concentrated in green loans. Investors reduce the number of non-green loans in industries with targets. Divestors reduce non-green loans as well, but do not change the number of green loans after setting targets. Greenwashers reduce non-green loans and increase green loans, but both statistical and economic significance are,e at best, marginal. Similarly, divestors and investors reduce lending the brownest firms, but greenwashers do not.

Our final test assesses whether loans by each bank category lead to a reduction in future emissions. In particular, we expect that if our classification is correct, then loans from 'investor' banks are most likely to transform the borrower's operations, leading to lower emissions. To test this hypothesis, we construct a variable that measures the strength of the prior relationship of a firm with the three different categories of banks. This prior exposure is calculated as the weighted average loans taken from each category of banks in a prior relationship period (2010-2014). We show that this instrument is valid in that prior exposure predicts future realized exposure. We find that prior exposure to investor banks predicts a decline in both absolute and intensity-based measures of emissions after targets are set. These results survive a range of including firm, SIC2-year, and Country-Year fixed effects. These fixed effects help rule out a range of alternative interpretations. Exposure to divestors is not related to emissions, while exposure to greenwashers predicts a relative increase in emissions in 4 out of 8 specifications and no change in the remaining 4 specifications.

We then test how these bank categories differ in their lending behavior along other dimensions. We find some evidence that banks of a given category are more likely to participate in the same syndicate after setting targets. In our most stringent specification this is only true for divestor banks. We also find that divestors are less likely to lend to high emitters, and even reduce lending to existing high emitting customers. Overall, we show that banks follow different strategies in this space and that ignoring this heterogeneity obfuscates the effects of financed emission targets for certain types of banks.

We contribute to the nascent literature examining the economic impacts of firms' emissions commitments. As discussed above, our work is closely related to Kacperczyk and Peydró (2022) and Sastry, Verner, and Ibanez (2024) that find conflicting evidence on the effects of bank emissions targets on lending. We differ from these papers because we analyze quantitative industry-specific emissions targets set by each bank and characterize the heterogeneity in bank strategies in this space. Our paper is also related to recent work by Green and Vallee (2022), who examine the effects of banks' decisions to phase out lending to the coal industry. Our work differs in that we examine all industries with targets and the target-setting process.

2. Hypothesis Development

Following standard economic theory, in the absence of corporate governance conflicts between managers and shareholders, a bank should be expected to commit to financed emissions targets if such a commitment is viewed as profit enhancing, for example by reducing legal costs in the face of regulatory pressure or by enhancing revenue in the face of consumer pressure to commit to environmental targets. Managers themselves may face social pressure to commit to improving a bank's environmental footprint. Whether or not corporate governance conflicts matter for the setting of environmental goals depends on whether pressures on managers meaningfully deviate from pressures on the entire organization so that managers are tempted to declare goals that reduce profitability.

Environmental activists have historically advocated for divestment from fossil fuel and other high carbon emitting industries. The financial case for divestment is that divestment by a sizable portion of investors is claimed to increase the cost of capital for targeted firms. By reducing the net present value of potential projects across the board, divestment would then cause targeted firms to shrink and their absolute emissions to decline due to that shrinkage. The effectiveness of divestment crucially hinges on the assumption that financial markets are imperfectly competitive so that targeted firms cannot easily obtain funding from non-divesting capital suppliers at the same cost as before (Teoh, Welch, and Paul (35-89); Heinkel, Kraus, and Zechner (2001)). From banks' perspective, everything else equal, divestment is profit reducing since fewer loans are funded in total. Therefore, divestment is either the consequence of a corporate governance conflict, or everything else is not equal so that banks can make up for lost revenues either by shifting to lending to other firms or by gaining other types of business e.g., attracting environmentally conscious customers (Dursun-de Neef and Ongena, 2023). Another possibility is that such banks believe that high-emitting firms are riskier because they are exposed to physical or transition risks from climate change.

An alternative approach to pursuing environmental goals for banks is through engagement or, more precisely, transformative investment that aids borrowers in carrying out projects that reduce carbon emissions. With regards to carbon emissions, this type of investment can come in two forms. One possibility is that the funded project increases the size of the borrowing firm albeit at a lower carbon footprint than its extant projects. In this case, the borrower's emissions intensity would decline but its absolute emissions would increase. Note that environmental benefit ultimately hinges on a decline in global absolute emissions. The aforementioned project would reduce global absolute emissions if older projects are eventually phased out or if the funded firm is able to grow at the expenses of firms that produce higher carbon emissions. A second possibility is that the funded project reduces the carbon footprint of the borrower's current projects, directly leading to a decline in both absolute emissions and emissions intensity. So long as capital invested in transformative projects is priced competitively, transformative investment is compatible with profit maximization in a bank's loan business. However, if consumers believe divestment to be more effective or if they do not trust that transformative investment is truly transformative, it is not clear that transformative investment is the overall profit maximizing solution. That said, transformative investment either enhances both the bank's and management's social standing or it reduces both. Thus, we do not expect such investment to be an outcome of corporate governance conflicts.

Finally, banks may engage in greenwashing. Greenwashing attempts to deal with regulatory and/or consumer-driven environmental pressure by signalling environmental friendliness without changing actual behavior. We can conceive of three ways in which greenwashing may preserve profits for banks. Either regulators and/or consumers are naive and cannot detect that greenwashing is taking place. Given the large number of news articles about greenwashing, this explanation seems unlikely. Second, greenwashing may be a short-term response to regulatory pressure. In this case, maximize the present value of profits through minimal compliance with regulators' demands, anticipating that regulation may tighten later on. Third, for greenwashing to work at longer horizons despite external pressures, greenwashing needs to mimick transformative investing such that consumers and/or regulators have difficulty determining whether a specific bank is greenwashing.

The extant literature largely focuses on the average effect of financed emissions targets on lending behavior and emissions and finds little effect in the average. However, financed emissions goals are relatively new to the banking industry and banks, regulators as well as consumers are simultaneously learning about their effects. Heterogeneous beliefs among banks about which strategy is profit maximizing as well as heterogeneity in social and regulatory pressure or corporate governance issues may cause multiple strategies to coexist in the marketplace. Indeed, as outlined above, the long-run effectiveness of the greenwashing strategy is unclear if no transformative investment ever occurs. Importantly, even if financed emissions targets are currently ineffective in the aggregate, so long as one of the strategies does produce lower emissions, regulatory and consumer pressures might ultimately result in convergence upon that strategy.

We thus set out to distinguish which banks pursue which strategy and analyze their impacts. Note that we expect all types of banks to target brown industries since they want to either maximize their ability to create change or the appearance of change. Because greenwashers do not pursue real change, we hypothesize that these banks declare financed emissions goals that look good, but are easy to meet. One way to do so is to declare targets primarily for industries that already have a negative emissions trend and set the target loosely enough so that the borrower industry will meet the target even if the bank does nothing. Therefore, we hypothesize that after controlling for borrower industry trends, greenwashers do not change their lending behavior and their environmental targets have no impact on borrowers beyond pre-existing borrower industry trends.

Unlike greenwashers, we hypothesize that both divesters and transformative investors pursue a decline in carbon emissions, albeit in different ways. Divesters are characterized by cutting lending to targeted industries. Because they are actively trying to benefit the environment, we expect their financed emissions targets to be strict relative to industry trends as well as relative to greenwashers. We expect these banks to reduce lending to the brownest firms within an industry. As outlined above, whether these lending cuts result in reduced firm size and reduced emissions is an empirical question and depends on substitution with other sources of external financing and the extent to which brown firms reduce environmental mitigation efforts to raise capital internally.

Transformative investors are characterized by increasing lending to targeted industries. Like divesters, we expect transformative investors to set strict goals since otherwise their efforts make no difference to borrower industry level emissions. We expect transformative investors to increase lending to targeted industries, especially through loans funding environmentally friendly projects such as green loans. We also expect transformative investment to result in greater capital expenditures for borrowing firms that lead to a decrease in emissions intensity. As discussed above, whether or not transformative investment reduces emissions in the absolute is an empirical question.

3. Data

We begin by compiling a list of all financial institutions that ranked among the top 50 lead arrangers by deal count in either the US or the worldwide syndicated loan market from DealScan in at least one year during our sample period from 2010 to 2023.[4] Our sample includes 80 financial institutions, of which ten are non-banks.[5] For the sake of simplicity, and because we do not find

[4]During this period, these institutions are involved in 86.9% (71.5%) of all syndicated loans, 96.5% (88.5%) of US syndicated loans, and 82.9% (61.1%) of non-US syndicated loans based on deal count (deal volume).

[5]We use the Lender Parent ID variable in DealScan to identify lenders. We hand check the lender list and, in a few cases, manually assign different Lender Parent IDs to the same lender based on the lender parent names. For example, we combine "Sumitomo Corp of America" and "Sumitomo Mitsui Financial Group Inc."

any non-banks in our sample to have financed emissions targets, we refer to all sample institutions as "banks" hereafter. Through the DealScan-Lender Link table provided by Schwert (2018) and through manual matching, we are able to map 70 of these banks with Compustat.

We next hand collect financed emissions targets for these banks from their TCFD, ESG, and similar climate or sustainability reports. For each financed emissions target, we record the targeted industry, the year in which the target was set, the year by which the target is intended to be met, whether the target covers scope 1/2/3 emissions, the baseline emissions amount and measurement units, and the targeted reduction in emissions.[6] We also record any self-reported progress numbers towards the target. Some of these reports do not provide SIC/NAICS codes for targeted industries. To the best of our ability, we assign SIC codes to targeted industries mentioned in these climate reports. To minimize industry mis-classification, we define a target industry at the 2-Digit SIC code level.

In addition to data on bank financed emissions targets, we collect data on the syndicated loans originated by our sample of banks between 2010 and 2023 from DealScan.[7] To be included in this loan sample, we require that the borrower is in Compustat and that the deal type is a revolver or term loan.[8] We map DealScan borrowers to Compustat using several sources. Our primary source is the link table from Chava and Roberts (2008).[9] Our second source of links relies on the DealScan to Worldscope link table used in Beyhaghi et al. (2021) coupled with CUSIP/ISIN/Sedol matching between Worldscope and Compustat. Finally for borrowers that we could not match through either

[6] Because banks report targets in different units, we standardize the units in each industry to make it comparable across banks.

[7] We use the period from 2010 to 2014 to measure pre-existing relationships between firms and banks.

[8] We exclude short term and other credit types, such as "364-Day Facility", "Murabaha", "Standby Letter of Credit", and "Export Credit". This restriction drops approximately 12% of deal count.

[9] The January 2021 version of this table is based on an older version of DealScan data. To connect tranches between the older and newer versions of DealScan, we use WRDS's wrds_loanconnector_ids file.

of these link table, we employ a fuzzy name matching algorithm, using SAS's COMPGED function, to match borrowers in DealScan with firms in Compustat. We manually review the list of potential matches with the smallest spelling distance and retain those that are accurate.

All told, this loan sample includes 35,881 unique deals in 10,550 unique firms.[10] This sample covers 90.2% (79.5%) of all syndicated loans with a borrower in Compustat, 97.3% (90.5%) of US syndicated loans with a borrower in Compustat, and 86.9% (70.3%) of non-US syndicated loans with a borrower in Compustat based on deal count (deal volume).[11] Following the literature, we allocate deal/tranche amounts among syndicate members on a pro-rata basis. We also adjust deal/tranche amounts for inflation using the CPIAUCSL series from FRED and report these amounts in 2020 US dollars.

Finally, we collect data on firm outcomes from standard sources. Specifically, we collect firm financial data from Compustat, firm emissions data from Trucost, and detailed data on firm capital structure from Capital IQ. Additional details are provided in Section A.1 of the Appendix.

4. Results

4.1. Evolution of emissions targets

After the TCFD published its recommendations in 2017, banks that intended to implement the recommendations typically started by first defining industries for which to measure emissions. They then designed and implemented a measurement framework before finally setting targets. Figure 1 shows the distribution of bank-industry years in which a bank first sets a financed emissions

[10] These figures are 19,178 unique deals in 7,450 unique firms for the period 2015 through 2023, which excludes the sample period we use to measure pre-existing relationships between firms and banks.

[11] We are able to match 38.0% (54.0%) of all syndicated loans to borrowers in Compustat, 41.1% (64.8%) of US syndicated loans to borrowers in Compustat, and 36.6% (47.3%) of non-US syndicated loans to borrowers in Compustat based on deal count (deal volume).

target in a given industry.[12] The first few banks to set targets did so in 2019. Thereafter, the number of targets set increases every year until 2022, during which roughly 42% of the 306 targets in our sample were set.

While not shown in Figure 1, foreign banks are considerably more likely to set emissions targets than US banks. About 90% of the targets in our sample are set by foreign banks, whereas only six US-domiciled banks have set any target by 2023. The first US-owned bank to set a target was JPMorgan Chase, setting targets for Oil & Gas, Electric Power, and Automotive Manufacturing in 2020.

Figure 2 provides further detail on the four industries that are most commonly subject to an emissions target: Electric, Gas & Sanitary Services (two-digit SIC code 49), Oil & Gas Extraction (13), Primary Metal Industries (33), and Transportation Equipment (37). Especially for banks that started setting targets relatively early, it is common to start with targets in one or two industries and then add targets for additional industries later. This pattern is apparent in that the Electric, Gas, & Sanitary Services industry, which includes Power Generation, was targeted sooner than the other industries by many banks, with 35 out of 74 targets set in the Top 4 industries in 2019-2021 covering that industry. The second most commonly targeted industry is the Oil & Gas Extraction industry, which is targeted one year after the Electric, Gas, & Sanitary Services industry at the median.

Further detail on all targeted industries is provided in Table 1. Note that an industry can be subject to more than one target by the same bank. For example, 42 banks have set 67 targets for the Electric, Gas, & Sanitary Services industry. Reasons include setting different targets for different time horizons, different subsectors of the industry, or emissions of different scope. Aside from the

[12] At the time of sustainability report collection in March 2024, the availability of 2023 reports was limited. Thus, 2023 target data are subject to change once these reports become available.

Top 4 industries described above, other targeted industries tend to involve real estate, various forms of transportation, cement, various types of mining, and agriculture. Many industries are targeted by only one bank, with e.g. Rabobank, a bank historically connected to agriculture, setting seven different agricultural targets. While a few banks set targets to be met as early as 2024 or 2025, the vast majority of targets are intended to be met by 2030.

An emissions target can either be an absolute target or an intensity target. An absolute target defines a certain total amount of emissions not to be exceeded, such as metric tons of CO_2. An intensity target sets emissions in relation to an economic output quantity, such as metric tons of CO_2 per metric ton of steel produced or kilograms of CO_2 per megawatt hour of electricity generated. An intensity target effectively constitutes an efficiency goal. The target can be met by producing the same amount of electricity with fewer emissions. However, it can also be met by focusing expansion of electricity generation on more emissions-efficient fuel sources while keeping old power plants in service and thus never actually reducing total emissions. An absolute target can only be met by reducing total emissions, either by increasing efficiency more than expanding production or by curtailing production. Most analyses of climate scenarios in which global warming is limited to 1.5°C involve actually reducing total emissions. By contrast, only 18% of banks' climate goals are absolute goals, with intensity goals being far preferred. Reduction of climate change thus depends on the intensity goals being stringent enough such that meeting them is not possible without reducing total emissions.

Emissions targets also differ in whether they cover scope 1, scope 2, and/or scope 3 emissions. Scope 1 emissions are covered in 88% of cases, scope 2 emissions in 65% of cases, and scope 3 emissions in 38% of cases. As one would logically expect, the extent to which scope 3 emissions are covered by emissions targets differs across industries depending on the extent to which emissions occur within the industry or downstream. For example, scope 3 emissions are covered for 81-87% of targets in the Coal Mining, Oil & Gas Extraction, and Transportation Equipment industries (which includes automotive manufacturing), where the bulk of emissions are produced when the production good is used. By contrast, emissions in the Agriculture, Cement, Metal, Water Transportation, Air Transportation, Power Generation, and Real Estate industries are primarily produced during that industry's production of its goods and in some cases its precursor products. Thus, scope 3 emissions tend to be de-emphasized in these industries.

4.2. Are banks setting stringent targets?

While the number of targets set by banks is important information, the climate impact of these targets depends on their stringency. To this end, Table 2 shows the distribution of reduction targets for the different industries. We first calculate the annualized reduction in the targeted metric that is required to be met by the target year (2030 in most cases). We also show how stringent the target is relative to a five-year exponentially-weighted moving average of emissions in that industry, as calculated using scope 1 and scope 2 emissions data from Trucost for the five years preceding the year in which the target was set.

The average annualized reduction target across all targets is 9.2%, with a median of 5.8%; however, there is considerable heterogeneity and skewness. The mean reduction is close to the first quartile reduction of 9.0%, indicating that some banks have very aggressive reduction targets. The third quartile is a much more moderate 3.5% reduction. Among the Top 4 targeted industries, the Oil & Gas Extraction industry is subject to mean and median reductions of 5.9% and 3.9%, respectively, often in terms of absolute emissions reductions. The median reduction is most aggressive for the Electric, Gas, & Sanitary Services industry at 7.9% (mean of 8.9%). By contrast, Primary Metals Industries are subject to a 7.6% average reduction despite a median and first quartile of 4.4% and 5.7%, indicating a small number of banks having a very aggressive reduction goal for this industry. Of note, the majority of banks targeting the Coal Mining industry target a 100% reduction in absolute emissions from this industry, which translates to an annualized target of about 44%.

Turning to the stringency of the reduction target relative to the industry-level emissions trend, Table 2 shows that many targets are not stringent, but rather coincide with prevailing trends already occurring in those targeted industries. The third quartile target requires an annualized reduction in emissions by 1.0% more than the industry trend, and 25% of all targets are not binding relative to the industry trend. Nonetheless, the mean reduction target requires reducing emissions by 8.6% per year relative to the industry trend, with a first quartile reduction of 10.4% per year, indicating that some targets are quite strict, calling for a 40-50% reduction over and above industry trends by 2030. For the majority of industries, the relative reduction target is less stringent than the annualized reduction target, indicating that these industries have already been reducing their emissions, or at least their emissions intensities.

Among the most frequently targeted industries, targets in the Primary Metal industries are binding relative to the industry trend in 35% of cases, with the median target failing to outpace the industry trend in emissions by 0.3% per year. Targets for Oil & Gas Extraction are binding relative to the trend in 67% of cases. Transportation Equipment and Electric, Gas, & Sanitary Services targets are more stringent, with 97% of targets binding relative to the trend in each industry.

4.3. Do emissions targets affect lending practices?

We next turn to the effect of emissions targets on bank lending. Figure 3 assesses what fraction of deals is covered by a target each year from 2019-2023. Initially, only about one percent of deals are covered, growing to five percent by 2021. Beginning in 2022, the number of covered deals starts to expand rapidly, with close to 17% of deals by volume covered by an emissions goal in 2023.

Figure 4 repeats the exercise from Figure 3 for deals originated in the four industries that are most frequently covered by a target. As discussed earlier, coverage of the Electric, Gas, & Sanitary Services industry increased sooner than for other industries, with about 20% of deal volume covered already in 2020, a number that increases to about 80% in 2022 and 2023. For Oil & Gas Extraction as well as Transportation Equipment, deal coverage increases from 10-15% in 2020 to about 70% in 2023. For Primary Metal Industries, coverage also increases over time, reaching a high point of a little over 60% in 2023. Note that there are potentially two opposing forces at play in the number of deals covered. As more banks define targets, the number of deals covered increases. However, if targets lead to a reduction in lending, the number of observed deals covered by a target would decrease.

To understand the extent to which emissions targets affect lending practices, we first seek to understand how banks that eventually define emissions targets differ from banks that do not define targets prior to any targets being set. Table 3 presents means and differences in means for several bank-level variables during the period from 2015-2018, before the first bank sets a target. Table 3 shows that banks that set targets are substantially larger than those that do not: target-setting banks have average total assets of 1.4 trillion US dollars compared to 125 billion for banks that do not set targets. Consequently, total deal volume originated for the average target-setting bank is larger (24.2 billion per year vs. 4.9 billion per year), primarily because each individual deal is larger (average deal size of 117 million vs. 8.5 million). The syndicated loan market share of the average bank that sets a target is 1.9%, compared to 0.4% for banks that do not set targets. Although we do not find any significant difference in average loan maturity across the two groups, target-setting banks do charge an all-in drawn spread that is 110 basis points lower than the 311 basis point spread charged by banks that do not set a target. Of course, this difference in spreads could capture fundamental differences, such as differences in borrower risk or greater economies of scale associated with larger deals.

Table 3 also shows data on loan portfolio emissions for the banks. We first compute a measure of absolute scope 1 emissions in millions of metric ton (MMT) CO_2 equivalents by taking a loan value-weighted average of firm scope 1 emissions across the bank's loan origination portfolio. This value-weighted average amounts to 5.5 MMT CO_2 equivalents for firms that borrow from target-setting banks and 2.3 MMT CO_2 equivalents for firms that borrow from banks that do not set a target, respectively. This difference is statistically significant. We also calculate scope 1 emissions intensity as metric ton CO_2 equivalents per one billion dollars of revenue. Although banks' actual targets typically divide by output quantities such as tons of steel, mega watt hours, or vehicle kilometers driven, using revenue in the denominator allows us to standardize intensities across industries. Although we do adjust for the effect of inflation on prices, we later use industry fixed effects and industry-year fixed effects to deal with the fact that output quantities have different prices in different industries, and the price differential could change over time. We do not see a statistically significant difference in the ex ante emissions intensity of the value-weighted average portfolio firm that borrows from a target-setting bank relative to a firm that borrows from another bank. Although the evidence of differences at the average is mixed, there is an ex ante difference at the right tail. Prior to setting any target, banks that end up setting a target are much more likely to lend to the brownest firms. Specifically, 24.8% of target-setting banks' loan volume is originated to firms in the top 20% of emitters, compared to 9.9% of the loan volume of banks that do not set targets. This difference is statistically significant at the 1% level.

Overall, we conclude from Table 3 that banks with and without targets are different from each other ex ante. Banks with targets are larger, are more likely to lend to the brownest firms, and although the average firm they lend to is not statistically significantly browner in intensity terms, a consequence of their greater market share is that they finance the bulk of emissions financed through the syndicated loan market.

Having established ex ante differences across banks that do and do not set targets, Table 4 assesses whether banks change their lending behavior after a target has been set. We construct Table 4 using a panel of bank-industry-year observations during 2015-2023. We regress outcome variables on an indicator of whether the bank has a financed emission target for an industry during the year in question as well as bank-SIC2 and SIC2-year fixed effects. We cluster standard errors at the bank-industry level. We first use an indicator for whether or not the bank makes any loan to an industry. Table 4 shows that the probability of any deal being originated does not significantly change after a bank initiates an emissions target for that industry. When we use the natural log of one plus the number of deals made, we find a reduction in deal count of about twelve percent. Average deal size also falls by roughly ten percent, but the change in total deal volume following the implementation of a target is indistinguishable from zero.

4.4. Classification of banks with targets

The results in Table 4 mask substantial heterogeneity in the effects of emissions targets on lending practices across banks with targets. While the average effect on lending is negative, some banks severely cut back on lending to industries with an emissions target, while other banks actually increase loan originations in targeted industries. In this section, we use this heterogeneity in ex post loan originations, in addition to the heterogeneity in target stringency, to classify banks with targets according to the classification schema developed in Section 2.

Specifically, we seek to classify banks with emissions targets into three broad categories: 1) divester banks, which pull back from targeted industries in order to reduce emissions; 2) (transformative) investor banks, which increase lending to target industries and engage with firms in those industries to reduce emissions; and 3) greenwasher banks, which signal environmental concern without actually changing behavior. To this end, we proceed using a data-driven k-medians clustering algorithm along two dimensions.

The first dimension captures target stringency. Specifically for each targeting bank, we calculate the bank's *Fraction of Loose Targets* as the weighted mean across targeted industries of a binary variable equal to one if the bank's industry target fails to outpace the industry trend in emissions (i.e., the bank's industry target has a positive relative reduction target), where the weights of each industry are given by the industry's share of the bank's total deal volume in the pre-period from 2015 to 2018. This dimension primarily helps to identify greenwasher banks, which declare emissions goals that are relatively easy to meet (say through prevailing trends in industry emissions), from targeting banks that declare more stringent targets.

The second dimension captures how banks change their lending behavior in an industry following the declaration of a target. In other words, this dimension provides some clarity as to the strategy a given bank will utilize in order to meet its emissions target. For a given bank, j, we calculate

$$Average\ Investment_j = \sum \omega_{i,j}(Targeted + \varepsilon_{i,j,t}), \tag{1}$$

where $\omega_{i,j}$ is proportional to the industry's share of the bank's total deal volume in the pre-period from 2015 to 2018, $Targeted$ is the coefficient estimated in Specification 3 of Table 4, $\varepsilon_{i,j,t}$ is the industry-bank-year residual from Specification 3 of Table 4, and the sum is taken across all industry-years in which the bank has a target in place.[13] Intuitively, this variable provides an estimate of a bank-specific analogue to the pooled estimate $Targeted$, where a bank that increased (decreased) deal volume in targeted industries following the declaration of a target would have a positive (negative) *Average Investment*. This dimension primarily helps to identify investor banks, which increase loan originations in targeted industries, from divester banks, which pull back from industries in which they set a target.

Figure 5 plots these two classification variables as well as the results of the *k*-medians clustering algorithm.[14] Interestingly, the clustering algorithm splits banks into three types with an equal number of banks belonging to each type. Greenwasher banks have relatively loose targets and on average increase loan originations to targeted industries. The other two types of banks, investors and divesters, have relatively stringent targets and primarily differ along the dimension of the strategy they employ to reduce their financed emissions. Divester banks reduce loan originations in

[13] We note here that we value-weight the $Targeted$ estimate and the residuals from an ordinary least squares regression. The values of $Average\ Investment_j$ and the results of the clustering algorithm are quantitatively similar if $Targeted$ and $\varepsilon_{i,j,t}$ are obtained from a weighted least squares regression where observations are weighted by deal volume in the pre-period.

[14] We standardize the two variables to have a mean of zero and a standard deviation of one. Additionally, we run the clustering algorithm across 2,500 random starting values to help ensure that we have found a global, rather than local, minimum.

targeted industries, while investor banks increase loan originations in targeted industries.

Having classified the types of banks that set emissions targets, we revisit the bank-industry-year results presented in Table 4. Table 5 replaces the single *Targeted* variable with a separate *Targeted* variable for each type of bank.[15] Specification 1 looks at the propensity to participate in loans to a given industry following the introduction of an emissions target. Both greenwasher and investor banks are more likely to participate in a loan to a given industry following the introduction of an emissions target in that industry. Divester banks reduce their propensity to lend following the introduction of an emissions target but the reduction is not statistically different from the average reduction in the propensity to lend to that industry by non-targeting banks.

We next turn to the propensity to lend on a pro-rata and institutional basis in Specifications 2 and 3 of Panel A, respectively. Here we observe that greenwasher banks increase their propensity to lend on both a pro-rata and institutional basis. Similarly, divester banks reduce their propensity to lend on both a pro-rata and institutional basis following the introduction of an emissions target; although they pull back more for institutional loans. Turning to deal counts and deal volume in Specifications 4 through 7, we see that investor banks participate in roughly 13 percent fewer deals by count; however, we do not observe a similar reduction in deal volume. Divester banks consistently pull back in terms of both deal count and deal volume. They reduce deal volume (count) by roughly 45 (18 percents) following the introduction of a target. Similar, pro-rata deal volume falls by roughly 44 percent while institutional deal volume falls some 56 percent.

Turning to average deal size in Panel B, greenwashers originate smaller deals on average fol-

[15] Here, we explore the impact of emissions targets on bank lending practices to targeted industries via OLS regressions. Given that this setting gives equal weight to industries both within and across banks, regardless of the relative deal volume in each bank-industry, we revisit these results within the context of weighted least squares (WLS) regressions in Section A.2 of the Appendix. Intuitively, the WLS results should better capture the effects of emissions targets on aggregate lending, although results are broadly consistent between the OLS and WLS regressions.

lowing the introduction of an emissions target with that decrease being driven by smaller pro-rata shares. Investor banks originate 12 percent smaller pro-rata shares on average post-introduction of a target, but institutional shares remain broadly similar such that average deal size for investor banks do not change significantly. Specifications 5 and 6 look at loan characteristics. We do not observe changes in loan maturity or loan prices following the introduction of emissions targets by any of our bank types.

In Panel A of Table 6, we rerun the propensity and deal volume analyses separately for the subsample of green and non-green loans. Broadly, we see that divester banks reduce their lending primarily in the non-green loan market segment. Conversely, increases in lending by investor banks observed in the full sample are driven primarily by an increase in lending in the green loan market segment, especially in terms of pro-rata deal volume. Evidence for greenwasher banks is more mixed.

Panels B and C of Table 6 investigates differences in the effects of emissions targets on lending practices between the top quintile emitters and cleaner (not top quintile) firms. We begin in Panel B by identifying top emitters within industry. Investor and divester banks seem to reduce lending both for top quintile emitters and the set of cleaner firms, although the reductions tend to be larger in absolute terms for firms that are relatively dirty. Greenwashers on the other hand seem to shift lending from dirtier firms in a given industry to relatively cleaner firms in that industry in order to reduce their overall portfolio emissions. Panel C sorts emitter firms across industries. For investor and divester firms, the patterns in Panel B hold broadly.

4.5. Do changes in lending practices matter for firms?

We next explore the impact of financed emissions targets on both financial and real firm-level outcomes. We investigate these effects in a panel of firm-year observations. Our primary variable of interest is $TgtLoan$ and is defined separately for each of our three bank types. $TgtLoan_{GW}$ is equal to the fraction of the firm's bank debt originated by a greenwasher bank that has a financed emissions target in the firm's industry.[16] $TgtLoan_{Inv}$ and $TgtLoan_{Div}$ are similarly defined for investor and divester banks. We note that these $TgtLoan$ variables can vary through time for multiple reasons, including: a bank may implement a target in a firm's industry where the firm already has a loan from that bank, a firm may take out a new loan from a bank with a target, a firm may reduce its exposure to a bank with a target by taking out a new loan from a bank without a target, or a firm may have an existing loan fall out of its capital structure.

We instrument for the $TgtLoan$ variables using a set of $Exposure$ variables based on relationship lending following the extant banking literature. Specifically,

$$Exposure_{GW,i,t} = \sum_j \omega_{i,j} \cdot hasTgt_{i,j,t} \cdot I(Type_j = \text{“}Greenwasher\text{”}) \tag{2}$$

where firm i's exposure to greenwasher banks at time t is a function of: a weight, $\omega_{i,j}$, specific to a firm-bank pair; a binary variable, $hasTgt_{i,j,t}$, equal to one if bank j has an emissions target in firm i's industry at time t, and zero otherwise; and a indicator variable, $I(Type_j = \text{“}Greenwasher\text{”})$, capturing whether bank j is of the type “Greenwasher”. For a given bank-firm pair, the weight is equal to the fraction of the loan volume to firm i over the relationship period originated by bank

[16] We assume that newly originated loans remain in the firm's capital structure for 60 months and calculate the $TgtLoan$ variable in June of each year. Results are quantitatively similar using 36 months or the maturity of the loan where available. When the maturity of the loan is not available from Dealscan with use the median loan maturity.

j. We define $Exposure_{Inv,i,t}$ and $Exposure_{Div,i,t}$ similarly by replacing the logical test of the bank's type with the appropriate type: $I(Type_j = \text{“}Investor\text{”})$ and $I(Type_j = \text{“}Divester\text{”})$, respectively.

Our two-stage least squares (2SLS) regressions thus take the form

$$Y_{i,t} = \mu_i + \eta_{k,t} + \beta_1 \cdot Tgt\widehat{Loan}_{GW,i,t} + \beta_2 \cdot Tgt\widehat{Loan}_{Inv,i,t} + \beta_3 \cdot Tgt\widehat{Loan}_{Div,i,t} \tag{3}$$

where $Y_{i,t}$ is a firm-level outcome variable, μ_i is a firm-level fixed effect, $\eta_{k,t}$ is a industry-year fixed effect, and the $\widehat{TgtLoan}$ variables are fitted value from the first-stage regressions. In the case of $TgtLoan_{GW,i,t}$, the first stage regression is given by

$$TgtLoan_{GW,i,t} = \mu_i + \eta_{k,t} + \delta_1 \cdot Exposure_{GW,i,t} + \delta_2 \cdot Exposure_{Inv,i,t} + \delta_3 \cdot Exposure_{Div,i,t} \tag{4}$$

where fixed effects are included at the same levels as in the second-stage regressions.

Table 7 reports results for these first-stage regressions. In each case, the *Exposure* variable is positively and significantly related to the corresponding $TgtLoan$ variable – e.g., $Exposure_{GW}$ is positively and significantly related to $TgtLoan_{GW}$. These relationships persist after controlling for the other *Exposure* variables as in the even-numbered specifications. In short, firms tend to borrow more from banks that have borrowed from in the past, and this relationship is relatively strong with first-stage F statistics well above standard rules of thumb or the critical values of Stock and Yogo (2005).

Table 8 presents the reduced form estimates of firm-level outcomes on the *Exposure* variables defined above. We begin with firm financial outcomes in Panel A. Bank debt actually increases in firms that are exposed to greenwasher banks. Note that this Capital IQ variable only includes on balance sheet debt and does not include undrawn commitments. A possible explanation, therefore, is that these firms become more financially constrained and draw down on pre-existing lines of credit. We find some evidence that firms exposed to divester banks with targets increase their cash holdings. This effect is consistent with these firms taking precautions against these divester banks pulling back from their lending relationships with these firms. Interestingly, interest expenses scaled by debt outstanding increases for firms with relatively large exposure to greenwasher banks with targets; however, this effect switches sign in the case of firms with a large exposure to investor banks.

Panel B of Table 8 focuses on real outcomes. We observe a reduction in tangible assets and investment in firms with a large exposure to divester banks with targets. Return on assets decreases for these firms by 31 basis points when a firm goes from no exposure to divester banks with targets to having all of their bank debt originated by these banks consistent with these firms disposing of profitable (but potentially dirty) assets. Firms that are exposed to investor banks on the other hand increase investment and see declines in their emissions in both absolute and intensity terms. Firms with exposure to greenwasher banks with targets see an increase in return on assets, as well as increases in both absolute and intensity emissions. This result could be consistent with the average brown firm cutting costs related to emissions mitigation in order to generate higher cash flows.

For both Panel A and B, the 2SLS results in Table 9 are consistent with these reduced form estimates. We also find quantitatively similar results using an alternative set of instruments where the bank-firm weights, $\omega_{i,j}$, in Equation 2 are based on the distance between a firm's headquarters and the bank's headquarters rather than prior lending decisions. These results are presented in full in Section A.3 of the Appendix.

One concern with the emissions results in Tables 8 and 9 is the potential for country-wide regulation or climate policies to drive changes in both firm emissions and bank emissions target setting. In Table 10, we attempt to rule out these alternative explanations. Specification 1 reproduces the reduced form estimate for the effects of our *Exposure* variables on absolute emissions. In Specification 2, we include country-year fixed effects to control for time variation in regulatory environment. Specifications 3 and 4 restrict the sample to exclude firms headquartered in countries in which banks with emissions targets are also headquartered. Across these three robustness checks, we see similar effects of investor bank exposure on firm absolute emissions. The right half of Table 10 repeats this exercise for emissions intensity. Again, it appears that the emissions intensity results in Tables 8 and 9 are not driven by these omitted variable concerns.

5. Additional Tests

5.1. Coordination between banks with emissions targets

In this section, we explore the extent to which banks with emissions targets coordinate their lending behavior. Nominally, we are interested in whether, for example, investor banks tend to work together by participating in the same loans, or whether divester banks tend to pull out of the same loans. We examine these relationships in a panel of bank-pair-industry-year observations. Our dependent variable is the fraction of deal volume in which both banks in the bank pair participate in the loan. Our variables of interest are indicator variables equal to one if both banks target emissions in the industry in a given year and if both banks are of given types – both greenwasher banks, one greenwasher bank and one investor bank, and so on. Our main specification controls for broad changes in a bank's lending to a given industry in a given year through the inclusion of bank-industry-year fixed effects for each bank in a given bank pair.

Panel A of Table 11 presents estimates for all syndicates. Beginning with Specification 1, we see that banks pairs in which both banks have targets tend to participate in a larger fraction of their loans together compared to either of those banks' average bank-pair. All type pair coefficients are positive, and with the exception of bank pairs with targets in which one bank is a divester and the other is an investor, statistically significant. Interestingly for each bank type, the level of coordination is highest with banks of the same type. For example, bank pairs with targets where both banks are greenwashers participate in roughly 20 percent more loans together (by deal volume) than average. This number is only 10.0% (15.9%) for pairs with a greenwasher bank and a divester (investor) bank. Moreover, a test of the equality of the coefficients for type pairs involving a greenwasher bank rejects the null that the coefficients $GW \times GW$, $GW \times Div$, and $GW \times Inv$ are equal. This finding holds for type pairs involving a investor bank ($Inv \times Inv = Div \times Inv = GW \times Inv$) and type paris involving a divester bank ($Div \times Div = Div \times Inv = GW \times Div$) as well. This provides some evidence that banks with targets know each other's types to some extent.

It may be that our results thus far are picking up time invariant features of a given bank pair. For example, it might be that a given bank pair have strategic complementarities either in general, or in a specific industry, that cause the banks to participate in relatively more loans together. In the extreme, our analysis might omit a variable that drives both banks in the pair to be a specific type. Specifications 2 and 3 of Panel A rule out some of these alternative explanations through the addition of bank-pair and bank-pair-industry fixed effects, respectively. In our tightest setting (Specification 3), only the $Div \times Div$ coefficient is significant with these bank pairs participating in roughly 12 percent more loans together after both implementing a target relative to before.

Specifications 4 through 6 repeat this analysis having restricted the loan sample to only green loans. Broadly, the coefficient estimates are similar to those obtained in the full loan sample. It does seem that participation in the green loan market may signal similar information as a bank type in that we fail to reject the Wald test of equality of coefficients in each of these specifications.

Finally, Panel B of Table 11 presents estimates for syndicates in which the banks are lead arrangers. Again, results are similar to those in Panel A for the full sample (Specifications 1 through 3). We fail to find evidence of coordination between banks with targets in the green loan sample.

5.2. Bank targets, lending, and firm emissions

In the subsample analysis in Section 4.4, we provided some preliminary evidence of how emissions targets interact with firm emissions to affect the lending practices of banks. In this section, we revisit this question in a panel of loans rather than in the bank-industry-year panel that we analyzed before. One drawback of this analysis is that we only observe loans that are originated and do not observe firms that try to obtain bank financing but fail to match with a lender.

Panel A of Table 12 examines how the propensity of a bank participating in a loan with a given firm changes with the introduction of an emissions target in that firm's industry. We construct a bank-loan dataset where are dependent variable is a participation variable equal to one if the bank participates in the syndicate for a given loan, and zero, otherwise. Our variables of interest are binary variables equal to one if a bank has an emissions target in a firm's industry and is of a given type. In Specification 1, we see that greenwasher banks are more likely to participate in a loan to a given firm after introducing an emissions target. On average, a greenwasher bank is roughly one percent more likely to participate in a loan following the introduction of an emissions target, which is a large effect relative to the unconditional mean of participating of roughly 5.5 percent. Conversely, divester banks are roughly one percent less likely to participate in a loan to a given firm following the introduction of an emissions target.

We next interact these *Targeted* variables with average firm emissions over the pre-period. We use these pre-period variables to avoid changes that firms may make to their emissions once banks introduce emissions targets from contaminating our coefficient estimates. We also note that the non-interacted emissions term (*Abs Scope 1* and *Int Scope 1*) are absorbed by the inclusion of the bank-firm fixed effects. In Specifications 2 and 3, we see that divester banks pull back from participating in loans for high emitter firms following the introduction of an emissions target. We do not see similar cross-sectional effects for either greenwasher or investor banks. We see little evidence in these specifications that divester banks are more sensitive to firm absolute emissions than intensity emissions after the introduction of an emissions target.

Specifications 4 through 6 examine these effects among the subsample of loans in which the firm and the bank had no pre-existing relationship – that is the bank participated in no loans to the firm during the relationship period of our sample. Here we see evidence that greenwasher banks expand the set of firms for which they participate in loans to. Greenwashers are roughly 1.6 percent more likely to participate in a loan to a firm with which they have no existing relationship with following the introduction of an emissions target. This effect is relative to an unconditional mean of roughly three percent for the non-relationship subsample.

In Specification 7, we look at these effects in the subsample of loans for which the bank and the firm had a pre-existing relationship. Divester banks seem to pull back to a much larger extent for firms that are their existing customers. In this case, divester banks are roughly seven percent less likely to participate in a loan to an existing customer following the introduction of an emissions target, relative to an unconditional mean of roughly 40 percent. This effect tends to be more pronounced in firms with relatively high absolute emissions as shown in Specification 7.

Panel B of Table 12 replaces the binary dependent variable in Panel A with the log of the lender share of the loan and focuses on bank-loan pairs in which the bank participates. In the full sample, we see evidence that both investor and divester banks reduce their lender share in loans to high emitter firms, both in absolute and in intensity terms, following the introduction of an emissions target. This reduction is more pronounced in new customers for divester banks and in existing customers for investor banks. In both cases, we see little evidence of a difference in sensitivity between absolute and intensity emissions for these banks.

Finally in Table 13, we investigate the impact of emissions targets on loan pricing. Here we construct a sample of loan-level observations where the dependent variable is the natural logarithm of the all-in drawn spread in basis points. Our primary variable of interest is the fraction of the overall deal volume originated by banks of a given type with an emissions target in the industry of the borrower firm, as well as the interaction of these $Fraction$ variables with firm-level emissions and a indicator variable for whether the loan is a green loan.

In Specification 1, we see that firms pay a roughly 37 percent higher spread when divester banks with targets underwrite the entire loan relative to when there are no divester banks with targets participating in the loan. This effect is broadly consistent with an equilibrium pricing outcome given the reduction in loan supply from divester banks following the introduction of an emissions target.

In Specification 2, we find some evidence of a "brownium" in loans to high absolute emitter firms. Firms with higher absolute emissions tend to pay lower spreads, and we see little in the way of differences in these spreads when participating banks have emissions targets. Admittedly, part of this "brownium" may be capturing differences in say the creditworthiness of the borrower firm, although we control for borrower credit rating and size. Evidence of this "brownium" goes away when we look at intensity emissions in Specification 3 – that is when we account for size somewhat more directly by scaling emissions by firm revenues. Interestingly, we do see evidence of a "brownium" when relatively more of the loan syndicate is comprised of divester banks with targets.

Specification 4 of Table 13 looks at pricing for green loans. Overall, we see some evidence of a "greenium" for green loans with green loans having roughly 25 percent lower spreads than similar non-green loans. This broader trend is not the case for green loans originated by investor banks. These loans are relatively higher priced on average. This evidence seems broadly consistent with investor banks participating in loans for which the firm might otherwise face difficulties in securing a green loan.

6. Conclusion

Can finance be a force for the greater good? Classical economic theory argues that individual firms acting in their own interests are not motivated to address externalities such as greenhouse gas emissions that cause climate change. Such externalities should be addressed by government action in the form of taxes or permits that put a price on the externality. At first glance, voluntary commitments by banks to unilaterally cut their portfolio emissions seem unlikely to succeed. What are the bank's incentives to reduce their portfolio's emissions if that means turning away valuable business? There are three possibilities. A portfolio with higher emissions has greater exposure to physical or transition risk related to climate change, and hence, banks may want to mitigate this risk by limiting their exposure. Second, banks may face pressure from their customers or depositors to improve their performance on climate-related metrics. Third, Serafeim (2018) argues that large asset managers such as index funds that hold the market have incentives to act as "stewards of the commons" because their success depends on the success of the market as a whole. Perhaps large global banks also have similar incentives since their lending portfolios span the market as well. On the other hand, turning down business may be hard if the benefits accrue in the long run, and banks may mitigate pressure from customers and managers by developing targets that do not bind in practice. Thus, the question of whether bank targets can make a difference is ultimately an empirical one.

We provide a first look at the distribution and stringency of financed emission bank targets across industries and banks. Our analysis suggests that given the heterogeneity in banks, the relative magnitudes of these forces differ and different banks achieve different outcomes. Some bank targets are stringent and some are not. Some banks choose to reduce lending to targeted industries, while others choose to lend to existing customers that are becoming greener. Thus, bank targets may help reduce emissions for some but not all banks and industries.

References

Abadie, A., J. Gu, and S. Shen. 2024. Instrumental variable estimation with first-stage heterogeneity. *Journal of Econometrics* 240:105425–.

Beyhaghi, M., R. Dai, A. Saunders, and J. Wald. 2021. International Lending: The Role of Lender's Home Country. *Journal of Money, Credit and Banking* 53:1373–416.

Chava, S., and M. R. Roberts. 2008. How Does Financing Impact Investment? The Role of Debt Covenants. *The Journal of Finance* 63:2085–121.

Dursun-de Neef, Ö., and S. Ongena. 2023. Climate change and bank deposits. *Available at SSRN 4657847* .

Ghysels, E., A. Sinko, and R. Valkanov. 2007. Midas regressions: Further results and new directions. *Econometric Reviews* 26:53–90.

Giroud, X., E. Liu, and H. M. Mueller. 2024. Innovation spillovers across u.s. tech clusters. *Working Paper* .

Green, D., and B. Vallee. 2022. Can Finance Save the World? Measurement and Effects of Coal Divestment Policies by Banks. *Working Paper* .

Heinkel, R., A. Kraus, and J. Zechner. 2001. The Effect of Green Investment on Corporate Behavior. *The Journal of Financial and Quantitative Analysis* 36:431–49–.

Kacperczyk, M. T., and J.-L. Peydró. 2022. Carbon Emissions and the Bank-Lending Channel. *Working Paper* .

Sastry, P. R., E. Verner, and D. M. Ibanez. 2024. Business as usual: Bank net zero commitments, lending, and engagement. Working Paper, National Bureau of Economic Research.

Schwert, M. 2018. Bank Capital and Lending Relationships. *The Journal of Finance* 73:787–830.

Serafeim, G. 2018. Investors as stewards of the commons? *Journal of Applied Corporate Finance* 30:8–17.

Stock, J., and M. Yogo. 2005. *Testing for weak instruments in linear iv regression*, 80–108. New York: Cambridge University Press.

Teoh, S. H., I. Welch, and W. C. Paul. 35-89. The effect of socially activist investment policies on the financial markets: Evidence from the south african boycott. *Journal of Business* 72:8–17.

Tobek, O., and M. Hronec. 2018. Does the source of fundamental data matter? *Working Paper* .

Figure 1: Distribution of Target Set Years for Bank Financed Emissions Targets

This figure plots the distribution of target set years for bank financed emissions targets in our sample. Details of our bank sample are in Section 3 of the text.

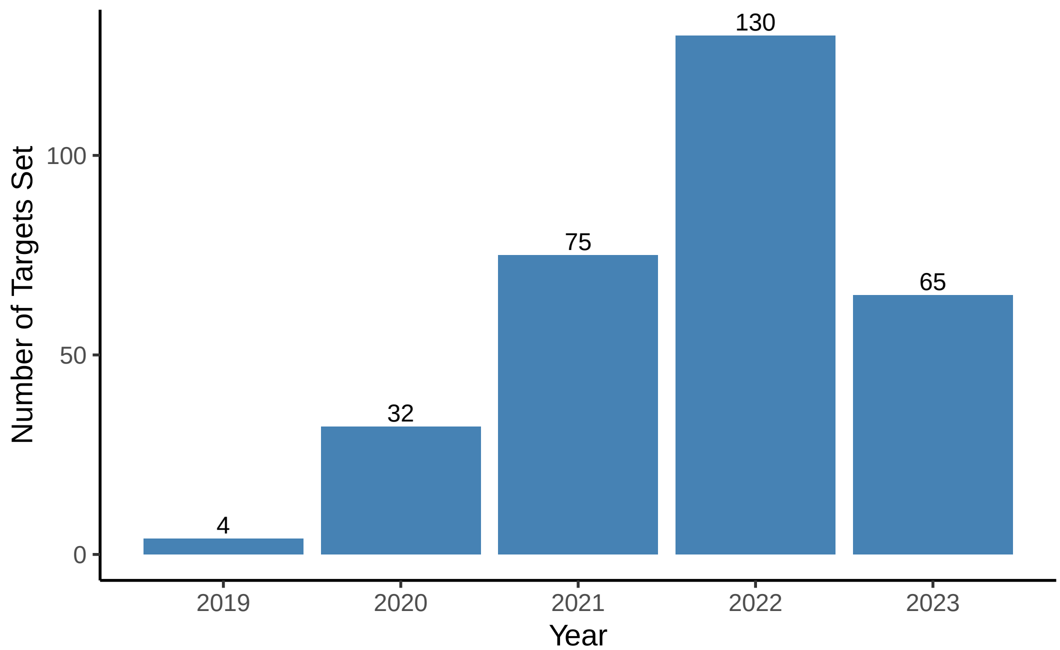

Figure 2: Distribution of Target Set Years – Top 4 Industries

This figure plots the distribution of target set years for bank financed emissions targets in our sample by industry. Included industries are the four two-digit SIC code industries with the greatest number of financed emissions targets. Details of our bank sample are in Section 3 of the text.

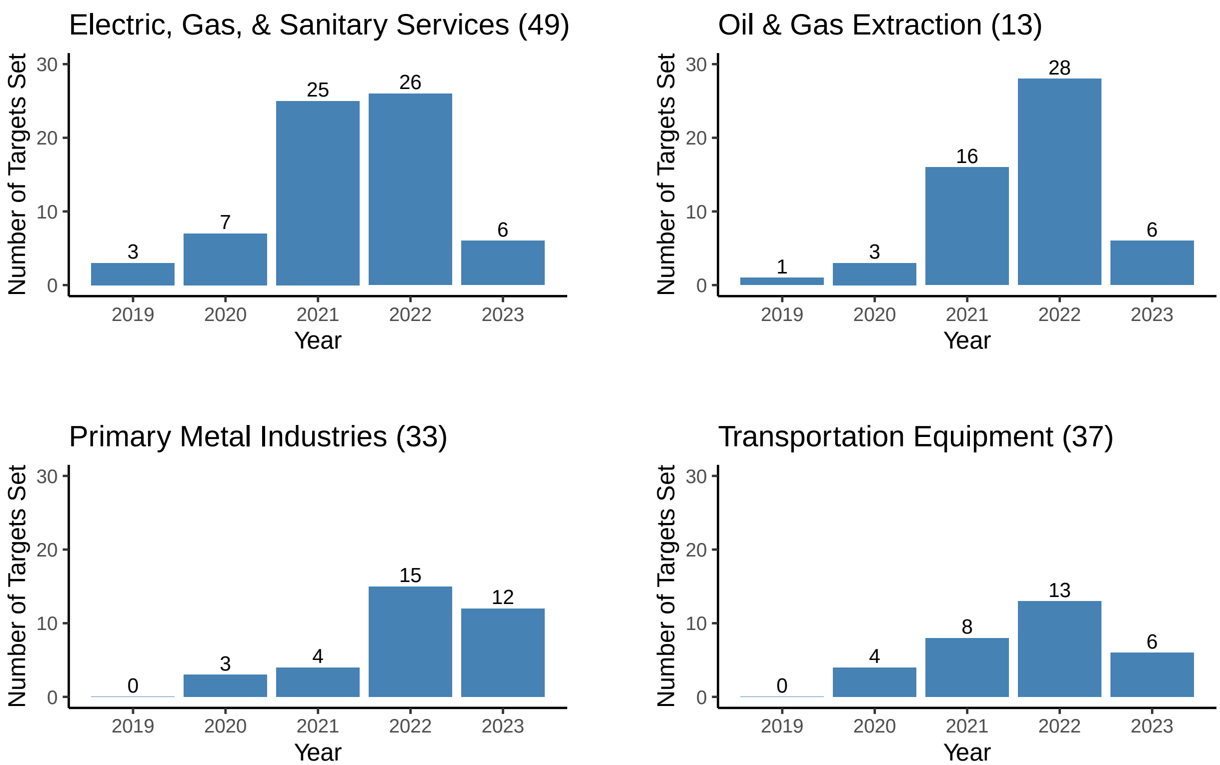

Figure 3: Percent of New Loans Covered by a Financed Emissions Target

This figure plots the ratio of originated loans covered by a financed emissions target to all originated loans in our sample by year. The solid blue line is based on the dollar amount of originated loans, while the dotted black line is based on the number of originated loans. We consider a loan to be covered by a financed emissions target if a bank in our sample has a financed emissions target in the same two-digit SIC code industry during the year in which the loan is originated. Details of our sample of banks and loans are in Section 3 of the text.

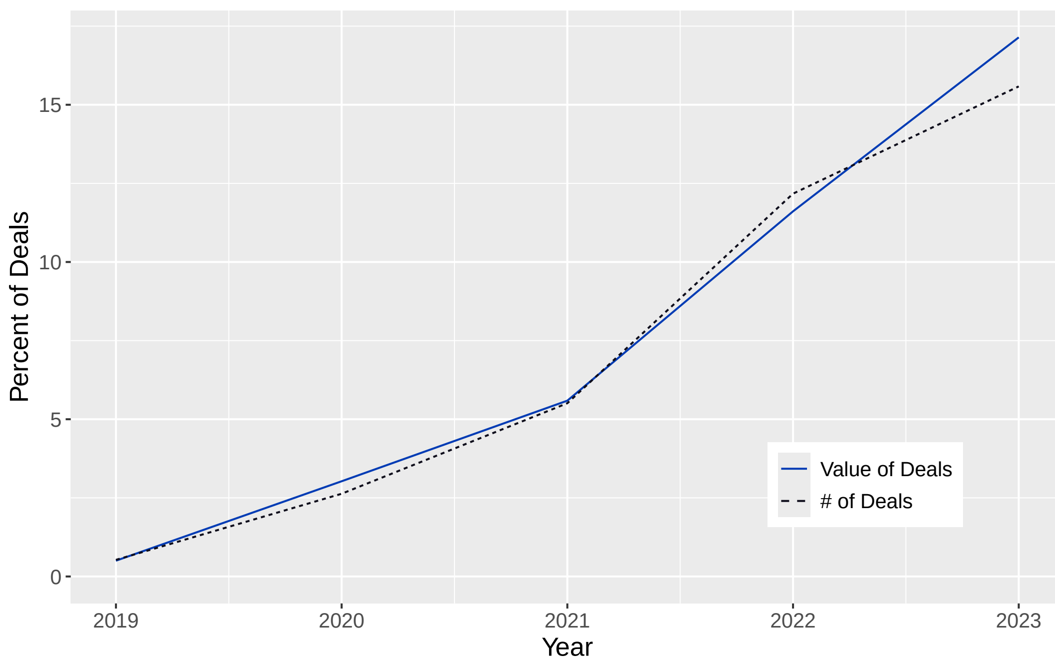

Figure 4: Percent of New Loans Covered by Target – Top 4 Industries

This figure plots the ratio of originated loans covered by a financed emissions target to all originated loans in our sample by year for several industries in our sample. Included industries are the four two-digit SIC code industries with the greatest number of financed emissions targets. The solid blue line is based on the dollar amount of originated loans, while the dotted black line is based on the number of originated loans. We consider a loan to be covered by a financed emissions target if a bank in our sample has a financed emissions target in the same two-digit SIC code industry during the year in which the loan is originated. Details of our sample of banks and loans are in Section 3 of the text.

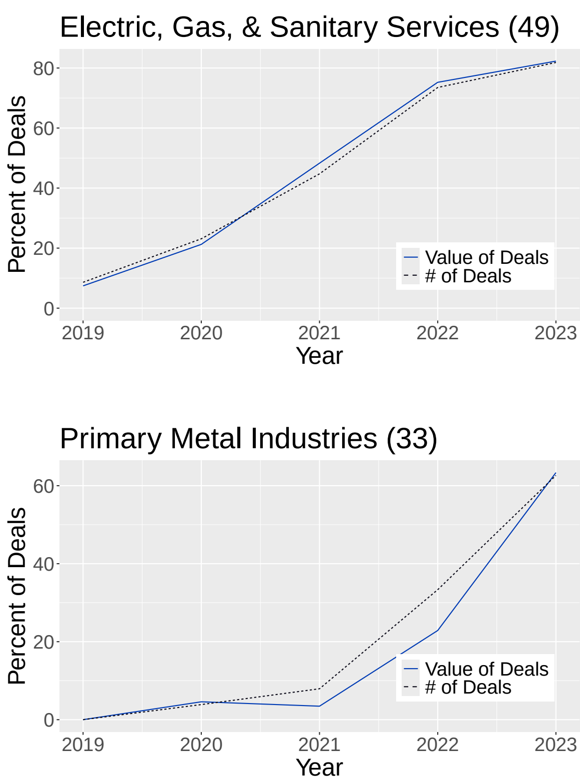

Figure 5: Cluster Analysis

This figure plots banks across the two dimensions used in our cluster analysis. *Fraction of Loose Targets* is equal to the fraction of the bank's targeted industries where the bank's emissions target is less stringent than the trend in the industry's emissions. *Average Investment* is the average change in lending to the targeted industry after the implementation of a target. Banks are classified following the cluster procedure outlined in Section 4.4.

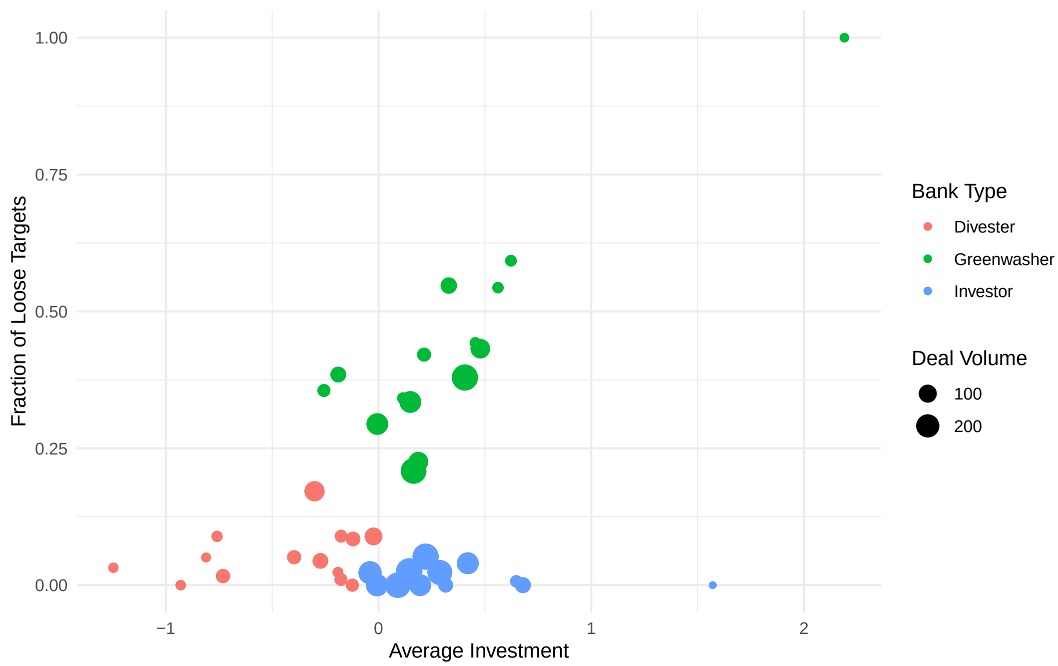

Table 1: Overview of Bank Financed Emissions Targets

This table presents summary statistics for the bank financed emissions targets in our sample by two-digit SIC code industry and pooled across all industries. *Number of Targets (Banks)* is the number of distinct financed emissions targets (banks that set a target) in a given industry in our sample. A bank may set multiple targets in a given industry; for example, a bank may set differential targets across locales or sub-industries. *Target Set Year* is the year in which the financed emissions target is set. *Target By Year* is the designated year for achieving a financed emissions target. *Fraction of Absolute Targets* is the number of targets that are based on absolute emissions scaled by the total number of targets. *Fraction of Scope 1 Targets* is the number of targets that consider Scope 1 emissions scaled by the total number of targets. The other scope variables are defined similarly.

	Number of		Target Set Year			Target By Year			Fraction of Targets			
2-digit SIC Code	Targets	Banks	First	Mode	Last	First	Mode	Last	Absolute	Scope 1	Scope 2	Scope 3
00 Agriculture	4	3	2020	2020	2023	2030	2030	2030	0.25	0.75	0.50	0.00
01 Agricultural Production – Crops	2	1	2022	2022	2022	2030	2030	2030	0.50	1.00	1.00	0.00
02 Agricultural Production – Livestock	9	2	2022	2022	2023	2030	2030	2030	0.22	1.00	0.56	0.00
10 Mining	2	2	2021	2021	2021	2030	2030	2030	0.50	1.00	1.00	0.50
12 Coal Mining	15	14	2021	2022	2023	2024	2030	2030	0.67	0.80	0.80	0.87
13 Oil & Gas Extraction	54	35	2019	2022	2023	2025	2030	2050	0.56	0.80	0.76	0.81
15 General Building Contractors	1	1	2022	2022	2022	2030	2030	2030	0.00	1.00	1.00	0.00
28 Chemicals & Allied Products	1	1	2023	2023	2023	2030	2030	2030	0.00	1.00	1.00	0.00
29 Petroleum & Coal Products	2	2	2020	2020	2022	2030	2030	2030	0.00	0.50	0.50	0.50
32 Stone, Clay, & Glass Products	17	16	2020	2022	2023	2030	2030	2030	0.00	1.00	1.00	0.06
33 Primary Metal Industries	34	24	2020	2022	2023	2030	2030	2050	0.06	0.97	0.97	0.12
35 Industrial Machinery & Equipment	1	1	2022	2022	2022	2030	2030	2030	0.00	1.00	1.00	1.00
37 Transportation Equipment	31	27	2020	2022	2023	2025	2030	2050	0.00	0.55	0.48	0.84
40 Railroad Transportation	2	2	2020	2020	2022	2030	2030	2030	0.00	1.00	1.00	0.50
41 Local & Interurban Passenger Transit	2	2	2020	2020	2023	2030	2030	2030	0.00	1.00	0.50	0.50
42 Trucking & Warehousing	1	1	2020	2020	2020	2030	2030	2030	0.00	1.00	1.00	1.00
44 Water Transportation	11	11	2020	2021	2023	2030	2030	2030	0.18	1.00	0.09	0.27
45 Transportation by Air	15	15	2020	2022	2023	2030	2030	2030	0.07	0.93	0.33	0.27
49 Electric, Gas, & Sanitary Services	67	42	2019	2022	2023	2025	2030	2050	0.09	0.94	0.42	0.16
61 Nondepository Institutions	6	6	2020	2023	2023	2030	2030	2030	0.00	0.83	0.83	0.00
65 Real Estate	29	20	2020	2023	2023	2030	2030	2030	0.00	0.97	0.79	0.10
All Firms	306	45	2019	2022	2023	2024	2030	2050	0.18	0.88	0.65	0.38

Table 2: Stringency of Financed Emissions Targets

This table presents summary statistics for the stringency of bank financed emissions targets in our sample by two-digit SIC code industry and pooled across all industries. *Number of Targets (Banks)* is the number of distinct financed emissions targets (banks that set a target) in a given industry in our sample. *Annualized Reduction Target* is the implied annual reduction required to meet a financed emissions target between the Target Set Year and the Target By Year. *Relative Reduction Target* is the difference between the *Annualized Reduction Target* and the current industry trend in emissions at the time the target is set. Current industry trends in emissions are the five-year exponentially-weighted moving average of Scope 1 and 2 emissions from Trucost. This relative measure uses trends in absolute emissions for absolute targets and trends in emissions intensity for intensity targets. We base industry trends on three-digit SIC code industries where there are at least ten firms in that industry. Otherwise, we fall back to two-digit SIC code industries, one-digit SIC code industries, or market-wide trends in order to have emissions data for at least ten firms in the trend calculation.

	Number of		Annualized Reduction Target				Relative Reduction Target				
2-digit SIC Code	Targets	Banks	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3	Fraction < 0
00 Agriculture	4	3	-0.047	-0.056	-0.041	-0.036	-0.053	-0.057	-0.051	-0.047	0.75
01 Agricultural Production – Crops	2	1	-0.090	-0.095	-0.090	-0.085	-0.082	-0.095	-0.082	-0.068	1.00
02 Agricultural Production – Livestock	9	2	-0.045	-0.023	-0.015	-0.013	-0.016	0.004	0.014	0.035	0.22
10 Mining	2	2	-0.058	-0.065	-0.058	-0.051	0.003	-0.038	0.003	0.043	0.50
12 Coal Mining	15	14	-0.442	-0.460	-0.438	-0.401	-0.367	-0.412	-0.390	-0.238	1.00
13 Oil & Gas Extraction	54	35	-0.059	-0.048	-0.039	-0.027	-0.069	-0.099	-0.074	0.018	0.67
15 General Building Contractors	1	1	-0.088	-0.088	-0.088	-0.088	0.039	0.039	0.039	0.039	0.00
28 Chemicals & Allied Products	1	1	-0.129	-0.129	-0.129	-0.129	-0.146	-0.146	-0.146	-0.146	1.00
29 Petroleum & Coal Products	2	2	-0.025	-0.029	-0.025	-0.021	-0.144	-0.193	-0.144	-0.095	1.00
32 Stone, Clay, & Glass Products	17	16	-0.034	-0.036	-0.031	-0.021	-0.047	-0.045	-0.040	-0.029	1.00
33 Primary Metal Industries	34	24	-0.076	-0.057	-0.044	-0.034	-0.045	-0.031	0.003	0.015	0.35
35 Industrial Machinery & Equipment	1	1	-0.006	-0.006	-0.006	-0.006	-0.124	-0.124	-0.124	-0.124	1.00
37 Transportation Equipment	31	27	-0.071	-0.080	-0.069	-0.054	-0.090	-0.099	-0.087	-0.072	0.97
40 Railroad Transportation	2	2	-0.054	-0.055	-0.054	-0.053	-0.084	-0.094	-0.084	-0.074	1.00
41 Local & Interurban Passenger Transit	2	2	-0.064	-0.077	-0.064	-0.050	-0.094	-0.096	-0.094	-0.091	1.00
42 Trucking & Warehousing	1	1	-0.021	-0.021	-0.021	-0.021	-0.039	-0.039	-0.039	-0.039	1.00
44 Water Transportation	11	11	-0.222	-0.401	-0.207	-0.030	-0.405	-0.567	-0.404	-0.236	0.91
45 Transportation by Air	15	15	-0.038	-0.048	-0.035	-0.028	-0.093	-0.152	-0.050	-0.040	0.93
49 Electric, Gas, & Sanitary Services	67	42	-0.089	-0.109	-0.079	-0.065	-0.074	-0.100	-0.073	-0.033	0.97
61 Nondepository Institutions	6	6	-0.073	-0.086	-0.074	-0.064	-0.080	-0.096	-0.074	-0.057	1.00
65 Real Estate	29	20	-0.076	-0.100	-0.076	-0.051	0.023	-0.004	0.027	0.058	0.31
All Firms	306	45	-0.092	-0.090	-0.058	-0.035	-0.086	-0.104	-0.062	-0.010	0.75

Table 3: Differences Across Banks With and Without Financed Emissions Targets

This table presents means and difference in means for several bank-level variables. All variables are measured in the pre-period of our sample (2015-2018). *# of Industries* is the number of distinct two-digit SIC code industries that the bank originates loans in during the pre-period. *Market Share (%)* is the percentage of loan value originated by a bank scaled by the total loan value originated across all banks in our sample. *Absolute Scope 1 Emissions (MMT CO_2e)* is the loan value-weighted average of firm Scope 1 emissions for loans originated by the bank in millions of metric ton CO_2 equivalents. *Intensity Scope 1 (MT CO_2e/\$B)* is the loan value-weighted average of firm Scope 1 emissions intensity for loans originated by the bank in metric ton CO_2 equivalents per \$B revenue. *% of Loans with Emissions Data* is the percentage of loan value originated by the bank with firm-level emissions data. *% of Loans to Brownest Firms* is the percentage of loan value originated by the bank with firm-level emissions data that is to firms in the top 20^{th} percentile of emitters. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Banks w/ Targets	Banks w/o Targets	Diff
# of Banks	45	33	–
# of Banks in CompuStat	31	23	–
# of Industries	55.733	33.758	21.976***
# of Deals Per Year	205.617	52.598	153.018***
Total Value of Deals Per Year (2020 \$B)	24.250	4.863	19.388***
Average Deal Size (2020 \$B)	0.117	0.085	0.032***
Market Share (%)	1.937	0.388	1.549***
Loan Maturity (mths)	61.491	61.181	0.310
All in Spread Drawn (bps)	201.581	311.859	-110.278^{***}
% US Banks	13.333	90.909	-77.576^{***}
Assets (2020 \$T)	1.392	0.125	1.266***
Leverage (%)	18.817	20.369	-1.552
Absolute Scope 1 Emissions (MMT CO_2e)	5.549	2.294	3.255***
Scope 1 Intensity (MT CO_2e/\$B)	0.325	0.236	0.089
% of Loans with Emissions Data	70.792	48.485	22.307***
% of Loans to Brownest Firms	24.809	9.862	14.947***

Table 4: Baseline Lending Regressions

This table reports the estimates for the impact of financed emissions targets on bank lending. The panel consists of bank-industry-year observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. *I(# Deals* > 0*)* is a binary variable equal to one if the bank originates a loan in the industry during the year of the observation, and zero otherwise. *Targeted* is a binary variable equal to one if the bank has a financed emissions target for the industry at any point during the year of the observation, and zero otherwise. Standard errors are clustered at the bank-industry level. Fixed effects are included to control for bank-industry and industry-year. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	I(# Deals > 0)	ln(1+ # Deals)	ln(1+ \$ Deals)	ln(\$ Avg Deal)
Targeted	0.0118	-0.1236^{***}	-0.1736	-0.0954^{**}
	(0.0205)	(0.0292)	(0.1059)	(0.0442)
Bank-SIC2 FEs	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y
N	68,100	68,100	68,100	20,033
R^2_{adj}	0.622	0.831	0.715	0.560

Table 5: Bank Classifications and Bank Lending

This table reports the estimates for the impact of financed emissions targets on bank lending by bank type. The panel consists of bank-industry-year observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. *I(# Deals* > 0*)* is a binary variable equal to one if the bank originates a loan in the industry during the year of the observation, and zero otherwise. Other indicator variables, denoted $I(\cdot)$, are similarly defined. $Targeted_{GW}$ is a binary variable equal to one if the bank is classified as a "Greenwasher" and has a financed emissions target for the industry at any point during the year of the observation, and zero otherwise. $Targeted_{Inv}$ and $Targeted_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. For an observation to be included in Panel B, the bank must have originated at least one loan in the given industry in the given year. Standard errors are clustered at the bank-industry level. Fixed effects are included to control for bank-industry and industry-year. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Propensity to Lend and Amount of Lending

	I(# Deals > 0)	I($ ProRata > 0)	I($ Inst > 0)	ln(1+ # Deals)	ln(1+ $ Deals)	ln(1+ $ ProRata)	ln(1+ $ Inst)
$Targeted_{GW}$	0.0599*	0.0921**	0.0641*	0.0017	0.1386	0.2833	0.0696
	(0.0315)	(0.0383)	(0.0373)	(0.0513)	(0.1688)	(0.1900)	(0.1851)
$Targeted_{Inv}$	0.0618**	0.0473	−0.0199	−0.1295***	0.0338	−0.0428	−0.2781
	(0.0296)	(0.0303)	(0.0449)	(0.0482)	(0.1645)	(0.1472)	(0.2232)
$Targeted_{Div}$	−0.0421	−0.0541*	−0.0903***	−0.1834***	−0.4538***	−0.4356***	−0.5631***
	(0.0292)	(0.0303)	(0.0318)	(0.0388)	(0.1447)	(0.1437)	(0.1589)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y
N	68,100	68,100	68,100	68,100	68,100	68,100	68,100
R^2_{adj}	0.622	0.599	0.545	0.831	0.715	0.700	0.624

Panel B: Average Deal Size and Loan Characteristics

	ln($ Deals)	ln($ ProRata)	ln($ Inst)	Pro Rata Share	ln(Maturity)	ln(All in Spread)
$Targeted_{GW}$	−0.1562**	−0.1675*	−0.0811	0.0299	0.0400	0.0076
	(0.0681)	(0.0860)	(0.0783)	(0.0318)	(0.0316)	(0.0495)
$Targeted_{Inv}$	−0.0881	−0.1227*	0.0246	−0.0091	0.0083	0.0583
	(0.0654)	(0.0680)	(0.0988)	(0.0284)	(0.0387)	(0.0517)
$Targeted_{Div}$	−0.0616	−0.0445	−0.1169	0.0349	−0.0374	0.0234
	(0.0596)	(0.0710)	(0.0869)	(0.0318)	(0.0368)	(0.0508)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y
N	20,033	17,677	14,174	20,033	19,936	14,770
R^2_{adj}	0.560	0.532	0.513	0.378	0.410	0.565

Table 6: Subsample Analysis

This table reports the estimates for the impact of financed emissions targets on bank lending by bank type for different subsamples of loans. The panel consists of bank-industry-year observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. $Targeted_{GW}$ is a binary variable equal to one if the bank is classified as a "Greenwasher" and has a financed emissions target for the industry at any point during the year of the observation, and zero otherwise. $Targeted_{Inv}$ and $Targeted_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Panel A considers green and non-green loans. Panel B considers brown loans, where brown loans are loans to firms in the top 20^{th} percentile of emitters within industry. Panel C considers brown loans, where brown loans are defined across all industries. Standard errors are clustered at the bank-industry level. Fixed effects are included to control for bank-industry and industry-year. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Green Loans

	ln(1+ # Deals)		ln(1+ \$ Deals)		ln(1+ \$ Pro Rata)		ln(1+ \$ Institutional)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Targeted_{GW}$	-0.0998^{*}	0.0769	-0.2078	0.4139^{*}	-0.0332	0.2796	-0.2023	0.2967^{*}
	(0.0563)	(0.0474)	(0.1984)	(0.2289)	(0.2025)	(0.2246)	(0.1929)	(0.1618)
$Targeted_{Inv}$	-0.2365^{***}	0.1103^{***}	-0.2531	0.5892^{**}	-0.3556^{**}	0.4678^{**}	-0.4921^{**}	0.2245
	(0.0523)	(0.0423)	(0.1784)	(0.2338)	(0.1553)	(0.2125)	(0.2250)	(0.1489)
$Targeted_{Div}$	-0.2649^{***}	-0.0426	-0.7907^{***}	-0.1625	-0.7257^{***}	-0.1781	-0.7518^{***}	-0.0495
	(0.0455)	(0.0319)	(0.1629)	(0.1574)	(0.1528)	(0.1407)	(0.1641)	(0.1114)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Non-green	Green	Non-green	Green	Non-green	Green	Non-green	Green
N	68,100	36,300	68,100	36,300	68,100	36,300	68,100	36,300
R^2_{adj}	0.819	0.534	0.705	0.477	0.690	0.454	0.614	0.325
Wald Test (p-Value):								
Equality of Coefs	0.045	0.004	0.019	0.006	0.013	0.014	0.078	0.098

Table 6: Subsample Analysis (cont.)

Panel B: Brownest Firms Within Industry

	ln(1+ # Deals)		ln(1+ $ Deals)		ln(1+ $ Pro Rata)		ln(1+ $ Institutional)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Targeted_{GW}$	−0.0193	−0.1582***	0.1449	−0.4093	0.4240**	−0.4111*	−0.1092	−0.5619***
	(0.0497)	(0.0529)	(0.1531)	(0.2575)	(0.1726)	(0.2373)	(0.1722)	(0.2153)
$Targeted_{Inv}$	−0.1423***	−0.1433***	−0.2777*	−0.3685*	−0.1769	−0.4625**	−0.2387	−0.5054***
	(0.0440)	(0.0383)	(0.1615)	(0.1928)	(0.1508)	(0.1963)	(0.2142)	(0.1765)
$Targeted_{Div}$	−0.0970***	−0.1127***	−0.3336**	−0.6463***	−0.2605**	−0.4304***	−0.1973	−0.4560***
	(0.0325)	(0.0272)	(0.1401)	(0.1418)	(0.1247)	(0.1290)	(0.1347)	(0.1112)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Cleaner	Brownest	Cleaner	Brownest	Cleaner	Brownest	Cleaner	Brownest
N	65,700	59,100	65,700	59,100	65,700	59,100	65,700	59,100
R^2_{adj}	0.761	0.708	0.640	0.638	0.611	0.606	0.539	0.516
Wald Test (p-Value): Equality of Coefs	0.142	0.657	0.029	0.427	0.002	0.983	0.873	0.899

Panel C: Brownest Firms

	ln(1+ # Deals)		ln(1+ $ Deals)		ln(1+ $ Pro Rata)		ln(1+ $ Institutional)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Targeted_{GW}$	−0.0547	−0.0319	−0.0560	−0.2244	0.1379	−0.0452	−0.2231	0.0284
	(0.0425)	(0.0512)	(0.1851)	(0.1932)	(0.1811)	(0.1933)	(0.1652)	(0.2192)
$Targeted_{Inv}$	−0.0579	−0.1419***	0.0336	−0.3190*	0.1062	−0.3506**	−0.0186	−0.3053
	(0.0454)	(0.0389)	(0.1756)	(0.1635)	(0.1632)	(0.1576)	(0.1858)	(0.1948)
$Targeted_{Div}$	−0.0361	−0.1630***	−0.2236*	−0.5147***	−0.1994*	−0.3783***	0.0392	−0.6227***
	(0.0298)	(0.0346)	(0.1326)	(0.1505)	(0.1146)	(0.1418)	(0.1095)	(0.1479)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Cleaner	Brownest	Cleaner	Brownest	Cleaner	Brownest	Cleaner	Brownest
N	67,200	59,200	67,200	59,200	67,200	59,200	67,200	59,200
R^2_{adj}	0.789	0.788	0.667	0.690	0.649	0.668	0.568	0.557
Wald Test (p-Value): Equality of Coefs	0.891	0.073	0.455	0.418	0.142	0.281	0.397	0.036

Table 7: Financed Emissions Targets and Firm Outcomes – First Stage

This table reports the estimates for the impact of a relationship with a bank with a financed emissions target on the fraction of a firm's bank debt originated by a bank with a financed emissions target. The panel consists of firm-year observations for the period 2015 to 2023. The dependent variable in the first two specifications is $TgtLoan_{GW}$ equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank that has a financed emissions target in the firm's industry. $TgtLoan_{Inv}$ and $TgtLoan_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. $Exposure_{GW}$ is equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank during the relationship lending period from 2010 to 2014. $Exposure_{Inv}$ and $Exposure_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Industries are defined at the two-digit SIC code level. Standard errors are clustered at the firm level. Fixed effects are included at the firm- and industry-year-level. First stage F-statistics for the 2SLS regression of log assets on the *TgtLoan* variables are reported. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	TgtLoan_{GW}		TgtLoan_{Inv}		TgtLoan_{Div}	
	(1)	(2)	(3)	(4)	(5)	(6)
$Exposure_{GW}$	0.0067***	0.0097***		−0.0066**		−0.0092***
	(0.0011)	(0.0024)		(0.0027)		(0.0022)
$Exposure_{Inv}$		−0.0019	0.0076***	0.0157***		−0.0026
		(0.0020)	(0.0010)	(0.0025)		(0.0022)
$Exposure_{Div}$		−0.0017		−0.0079***	0.0098***	0.0212***
		(0.0022)		(0.0026)	(0.0013)	(0.0023)
Firm FEs	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y
N	59,041	59,041	59,041	59,041	59,041	59,041
R^2_{adj}	0.334	0.334	0.408	0.411	0.301	0.311
First Stage F-stat	415.3	149.5	699.8	317.1	815.9	555.2

Table 8: Financed Emissions Targets and Firm Outcomes – Reduced Form

This table reports the reduced form estimates for the impact of financed emissions targets on firm outcomes. The panel consists of firm-year observations for the period 2015 to 2023. The dependent variables are defined in Table A.1. $Exposure_{GW}$ is equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank during the relationship lending period from 2010 to 2014. $Exposure_{Inv}$ and $Exposure_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Industries are defined at the two-digit SIC code level. Standard errors are clustered at the firm level. Fixed effects are included at the firm- and year-industry-level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Financial Outcomes

	Leverage	Bank Debt	Avail Credit	Cash	Int Exp
$Exposure_{GW}$	−0.0030	0.0082*	0.0027	−0.0010	0.0014***
	(0.0022)	(0.0046)	(0.0050)	(0.0013)	(0.0004)
$Exposure_{Inv}$	0.0020	0.0017	−0.0001	0.0004	−0.0009***
	(0.0020)	(0.0040)	(0.0047)	(0.0012)	(0.0003)
$Exposure_{Div}$	−0.0014	0.0014	−0.0017	0.0028**	0.0001
	(0.0026)	(0.0045)	(0.0054)	(0.0012)	(0.0003)
Firm FEs	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y
N	58,794	56,629	49,445	58,077	55,183
R^2_{adj}	0.801	0.680	0.763	0.778	0.704

Panel B: Real Outcomes

	Assets	PP&E	Capex	R&D	ROA	Abs Scope 1	Int Scope 1
$Exposure_{GW}$	−0.0072	0.0016	−0.0003	0.0000	0.0041***	0.0402*	0.0355*
	(0.0087)	(0.0018)	(0.0007)	(0.0001)	(0.0015)	(0.0209)	(0.0212)
$Exposure_{Inv}$	−0.0033	0.0009	0.0018***	0.0000	0.0007	−0.0465***	−0.0340**
	(0.0078)	(0.0017)	(0.0006)	(0.0001)	(0.0013)	(0.0168)	(0.0165)
$Exposure_{Div}$	−0.0064	−0.0048***	−0.0013*	0.0000	−0.0031**	−0.0165	−0.0045
	(0.0085)	(0.0018)	(0.0007)	(0.0001)	(0.0015)	(0.0253)	(0.0236)
Firm FEs	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y
N	59,041	57,692	57,570	58,282	58,157	40,790	40,785
R^2_{adj}	0.971	0.945	0.605	0.922	0.705	0.943	0.928

Table 9: Financed Emissions Targets and Firm Outcomes – 2SLS

This table reports the two-stage least squares (2SLS) estimates for the impact of financed emissions targets on firm outcomes. The panel consists of firm-year observations for the period 2015 to 2023. The dependent variables are defined in Table A.1. $TgtLoan_{GW}$ equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank that has a financed emissions target in the firm's industry. $TgtLoan_{Inv}$ and $TgtLoan_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. We instrument for these endogenous variables with a set of exposure variables based on relationship lending between the banks in our sample and the panel of firms. $Exposure_{GW}$ is equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank during the relationship lending period from 2010 to 2014. $Exposure_{Inv}$ and $Exposure_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Industries are defined at the two-digit SIC code level. Standard errors are clustered at the firm level. Fixed effects are included at the firm- and industry-year-level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Financial Outcomes

	Leverage	Bank Debt	Avail Credit	Cash	Int Exp
$TgtLoan_{GW}$	-0.3025	1.3264^{***}	0.2361	0.1012	0.0991^{***}
	(0.1874)	(0.4476)	(0.4687)	(0.1111)	(0.0322)
$TgtLoan_{Inv}$	0.0797	0.3330	0.0308	0.0638	-0.0462^{**}
	(0.1185)	(0.2766)	(0.2489)	(0.0740)	(0.0200)
$TgtLoan_{Div}$	-0.0589	0.2978	-0.0686	0.1665^{***}	-0.0063
	(0.1134)	(0.2286)	(0.2558)	(0.0599)	(0.0168)
Firm FEs	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y
N	58,794	56,629	49,445	58,077	55,183
R^2_{adj}	0.796	0.657	0.762	0.774	0.681
First Stage F-stats:					
$TgtLoan_{GW}$	154.7	146.7	104.0	147.1	149.5
$TgtLoan_{Inv}$	317.9	306.7	305.2	314.2	304.1
$TgtLoan_{Div}$	552.3	524.9	490.5	546.1	511.4

Table 9: Financed Emissions Targets and Firm Outcomes – 2SLS (cont.)

Panel B: Real Outcomes

	Assets	PP&E	Capex	R&D	ROA	Abs Scope 1	Int Scope 1
$TgtLoan_{GW}$	-1.6948^{**}	-0.0378	0.0249	-0.0009	0.3938^{***}	0.4837	2.2779
	(0.7881)	(0.1488)	(0.0634)	(0.0067)	(0.1485)	(2.6467)	(2.3425)
$TgtLoan_{Inv}$	-0.5164	0.0168	0.1104^{***}	-0.0014	0.0721	-4.3174^{**}	-2.9511^{*}
	(0.5178)	(0.0994)	(0.0347)	(0.0055)	(0.0856)	(1.6871)	(1.5071)
$TgtLoan_{Div}$	-0.6312	-0.2259^{***}	-0.0185	-0.0019	-0.0894	-1.7914	-0.6349
	(0.4427)	(0.0835)	(0.0355)	(0.0042)	(0.0770)	(1.3668)	(1.2114)
Firm FEs	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y
N	59,041	57,692	57,570	58,282	58,157	40,790	40,785
R^2_{adj}	0.970	0.944	0.594	0.922	0.673	0.938	0.924
First Stage F-stats:							
$TgtLoan_{GW}$	149.5	146.5	154.3	148.5	147.2	70.1	70.2
$TgtLoan_{Inv}$	317.1	314.9	314.4	319.8	318.5	163.2	163.3
$TgtLoan_{Div}$	555.2	540.5	542.5	542.7	546.1	463.1	465.2

Table 10: Financed Emissions Targets and Firm Emissions

This table reports reduced form estimates for the impact of financed emissions targets on firm outcomes. The panel consists of firm-year observations for the period 2015 to 2023. The dependent variables are defined in Table A.1. $Exposure_{GW}$ is equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank during the relationship lending period from 2010 to 2014. $Exposure_{Inv}$ and $Exposure_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Industries are defined at the two-digit SIC code level. Standard errors are clustered at the firm level. Fixed effects are included at the firm- and industry-year-, and country-year-level, as noted. Specifications 1 and 5 present the baseline specifications from Table 8. Specifications using the "Exclude" subsample omit firms headquartered in the same countries as banks with financed emissions targets. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Abs Scope 1				Int Scope 1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Exposure_{GW}$	0.0402*	0.0346	0.0371	0.0752*	0.0355*	0.0370*	0.0464	0.0693*
	(0.0209)	(0.0216)	(0.0332)	(0.0390)	(0.0212)	(0.0215)	(0.0337)	(0.0380)
$Exposure_{Inv}$	−0.0465***	−0.0435**	−0.0619***	−0.0608**	−0.0340**	−0.0310*	−0.0583**	−0.0625**
	(0.0168)	(0.0178)	(0.0238)	(0.0282)	(0.0165)	(0.0171)	(0.0254)	(0.0278)
$Exposure_{Div}$	−0.0165	−0.0107	0.0094	−0.0206	−0.0045	−0.0054	0.0231	0.0132
	(0.0253)	(0.0262)	(0.0325)	(0.0360)	(0.0236)	(0.0243)	(0.0303)	(0.0334)
Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FEs	N	Y	N	Y	N	Y	N	Y
Sample	Full	Full	Exclude	Exclude	Full	Full	Exclude	Exclude
N	40,790	40,790	9,271	9,271	40,785	40,785	9,269	9,269
R^2_{adj}	0.943	0.944	0.936	0.936	0.928	0.928	0.924	0.924

Table 11: Bank Pairs Analysis

This table reports the estimates for the impact of financed emissions targets on syndicate participation by bank pairs. The panel consists of bank pair-industry-year observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. The dependent variable is the ratio of the sum of the lender share of deals in which both banks participated divided by the sum of the lender share across all deals of each bank in the bank pair. $GW \times GW$ is a binary variable equal to one if both banks in the bank pair are "Greenwasher" banks and have a financed emissions target in the industry-year of the observation. Other variables of interest are similarly defined for the different types of bank pairs. Panel A considers all loans, whereas Panel B considers loans where the bank is a lead arranger. Standard errors are clustered at the bank pair-industry level. Fixed effects are included to control for bank-industry-year and bank pair and bank pair-industry as noted. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: All Syndicates

	Full Sample			Green Loan Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
$GW \times GW$	0.0987***	0.0574***	0.0176	0.1161*	0.0588	0.0022
	(0.0181)	(0.0158)	(0.0155)	(0.0599)	(0.0572)	(0.0663)
$Div \times Div$	0.1214***	0.0750***	0.0618***	0.2162***	0.2073***	0.1927
	(0.0264)	(0.0244)	(0.0238)	(0.0765)	(0.0790)	(0.1334)
$Inv \times Inv$	0.0833***	0.0064	−0.0221	0.1855***	0.0890*	0.0280
	(0.0176)	(0.0153)	(0.0141)	(0.0475)	(0.0456)	(0.0569)
$GW \times Div$	0.0500***	0.0349**	0.0208	0.0673	0.0460	0.0345
	(0.0166)	(0.0147)	(0.0145)	(0.0471)	(0.0474)	(0.0582)
$GW \times Inv$	0.0793***	0.0224**	−0.0128	0.1041***	0.0391	0.0077
	(0.0126)	(0.0109)	(0.0111)	(0.0377)	(0.0370)	(0.0454)
$Div \times Inv$	0.0153	0.0106	−0.0049	0.0468	0.0113	0.0268
	(0.0142)	(0.0129)	(0.0132)	(0.0410)	(0.0418)	(0.0557)
Bank$_i$-SIC2-Year FEs	Y	Y	Y	Y	Y	Y
Bank$_j$-SIC2-Year FEs	Y	Y	Y	Y	Y	Y
Bank$_i$-Bank$_j$ FEs	N	Y	N	N	Y	N
Bank$_i$-Bank$_j$-SIC2 FEs	N	N	Y	N	N	Y
N	154,721	154,721	154,721	45,677	45,677	45,677
R^2_{adj}	0.662	0.716	0.743	0.791	0.796	0.716
Wald Tests (p-Values):						
Equality of GW Coefs	0.016	0.422	0.201	0.828	0.849	0.642
Equality of Div Coefs	0.001	0.006	0.039	0.290	0.251	0.866
Equality of Inv Coefs	0.003	0.153	0.017	0.331	0.151	0.553

Table 11: Bank Pairs Analysis (cont.)

Panel B: Lead Arrangers

	Full Sample			Green Loan Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
$GW \times GW$	0.0744***	0.0417*	0.0445*	0.0285	0.0050	0.1255
	(0.0230)	(0.0219)	(0.0228)	(0.0771)	(0.0778)	(0.1059)
$Div \times Div$	0.0757***	0.0497*	0.0364	0.1265	0.0751	0.1494
	(0.0277)	(0.0278)	(0.0317)	(0.0891)	(0.0954)	(0.1520)
$Inv \times Inv$	0.0283	−0.0021	−0.0099	0.0391	0.0050	0.1169
	(0.0206)	(0.0196)	(0.0204)	(0.0481)	(0.0491)	(0.0809)
$GW \times Div$	0.0614***	0.0468***	0.0521***	0.0069	−0.0167	0.0909
	(0.0185)	(0.0180)	(0.0190)	(0.0573)	(0.0602)	(0.0836)
$GW \times Inv$	0.0452***	0.0145	0.0050	0.0270	−0.0036	0.0977
	(0.0152)	(0.0152)	(0.0163)	(0.0467)	(0.0488)	(0.0707)
$Div \times Inv$	0.0431**	0.0359**	0.0284	0.0586	0.0265	0.1463**
	(0.0173)	(0.0169)	(0.0181)	(0.0449)	(0.0478)	(0.0743)
Bank_i-SIC2-Year FEs	Y	Y	Y	Y	Y	Y
Bank_j-SIC2-Year FEs	Y	Y	Y	Y	Y	Y
Bank_i-Bank_j FEs	N	Y	N	N	Y	N
Bank_i-Bank_j-SIC2 FEs	N	N	Y	N	N	Y
N	139,436	139,436	139,436	32,705	32,705	32,705
R^2_{adj}	0.613	0.632	0.626	0.771	0.770	0.558
Wald Tests (p-Values):						
Equality of GW Coefs	0.580	0.782	0.816	0.781	0.745	0.743
Equality of Div Coefs	0.003	0.563	0.339	0.942	0.760	0.167
Equality of Inv Coefs	0.001	0.904	0.009	0.782	0.006	0.277

Table 12: Financed Emissions Targets and Loan Participation

This table reports the estimates for the impact of financed emissions targets on loan participation. The panel consists of bank loan observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. In Panel A, the dependent variable is binary variable equal to one if the bank participates in the loan, and zero, otherwise. In Panel B, the dependent variable is equal to the natural log of the bank loan in 2020 dollars, and observations where the bank does not participate in the loan are excluded. $Targeted_{GW}$ is a binary variable equal to one if the bank is a "Greenwasher" bank and has a financed emissions target in the firm's industry at the time of the loan. $Targeted_{Inv}$ and $Targeted_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Emissions variables are constant for each firm and are the natural logarithm of the average emissions over the 2015 to 2018 period. To be included in the relationship subsample, a bank must have participated in a loan to the firm over the relationship lending period from 2010 to 2014. Standard errors are clustered at the loan level. Fixed effects are included to control for bank-firm, industry-year and syndicate size. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Participation in Loan

	Full Sample			Non-relationship Subsample			Relationship Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Targeted_{GW}$	0.0111*	−0.0036	0.0048	0.0161***	0.0117	0.0134	−0.0154	−0.0857	−0.0209
$Targeted_{Inv}$	−0.0064	−0.0118	−0.0082	0.0001	0.0049	0.0004	−0.0195	−0.0712	−0.0174
$Targeted_{Div}$	−0.0123***	0.0370***	0.0066	−0.0051**	0.0113	0.0019	−0.0719***	0.0987	−0.0214
Abs Scope 1									
× $Targeted_{GW}$		0.0011			0.0004			0.0045	
× $Targeted_{Inv}$		0.0005			−0.0003			0.0035	
× $Targeted_{Div}$		−0.0036***			−0.0011			−0.0119*	
Int Scope 1									
× $Targeted_{GW}$			0.0013			0.0007			0.0003
× $Targeted_{Inv}$			0.0005			0.0001			−0.0002
× $Targeted_{Div}$			−0.0035***			−0.0010			−0.0095
Bank-Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Syndicate Size FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,548,253	1,114,991	1,114,991	1,440,303	1,023,383	1,023,383	107,950	91,608	91,608
R^2_{adj}	0.562	0.570	0.570	0.503	0.491	0.491	0.562	0.560	0.560

Table 12: Bank Switching Analysis (cont.)

Panel B: Amount of Loan

	Full Sample			Non-relationship Subsample			Relationship Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Targeted_{GW}$	−0.0364	0.5135	0.0710	−0.0901	0.8252	0.2569	0.0017	0.5946	0.0464
$Targeted_{Inv}$	0.0374	0.7758**	0.2949*	0.0712	0.0595	0.0902	0.0320	1.2229***	0.4252**
$Targeted_{Div}$	0.0463	0.8433***	0.3437**	0.1156	1.3103**	0.5554*	−0.0361	0.5898	0.1329
Abs Scope 1									
× *$Targeted_{GW}$*		−0.0376			−0.0637			−0.0402	
× *$Targeted_{Inv}$*		−0.0512**			−0.0021			−0.0799***	
× *$Targeted_{Div}$*		−0.0577**			−0.0915**			−0.0434*	
Int Scope 1									
× *$Targeted_{GW}$*			−0.0185			−0.0581			−0.0083
× *$Targeted_{Inv}$*			−0.0476*			−0.0096			−0.0681**
× *$Targeted_{Div}$*			−0.0556**			−0.0881*			−0.0294
Bank-Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Syndicate Size FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	85,128	65,677	65,677	40,793	27,908	27,908	44,335	37,769	37,769
R^2_{adj}	0.700	0.658	0.658	0.720	0.700	0.700	0.708	0.660	0.660

Table 13: Financed Emissions Targets and Loan Pricing

This table reports the estimates for the impact of financed emissions targets on loan prices. The panel consists of loan observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. The dependent variable is the natural logarithm of the all-in spread drawn in bps. $Fraction_{GW}$ is equal to the fraction of the loan volume originated by a "Greenwasher" bank with a financed emission target in the firm's industry. $Fraction_{Inv}$ and $Fraction_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Emissions variables are constant for each firm and are the natural logarithm of the average emissions over the 2015 to 2018 period. *I(Green Loan)* is a binary variable equal to one if the loan is green, and zero, otherwise. Standard errors are clustered at the loan level. Fixed effects are included to control for credit rating (including loans that are not rated) and year. These regressions additionally control for lagged log assets, leverage, interest coverage ratio, PP&E, ROA, current ratio, and cash flow volatility. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	(1)	(2)	(3)	(4)
$Fraction_{GW}$	0.2006	0.4017	-0.0765	0.2082
$Fraction_{Inv}$	-0.1846	0.6223	0.1906	-0.2416^{*}
$Fraction_{Div}$	0.3697^{*}	0.7215	2.0561^{**}	0.6995^{**}
Abs Scope 1		-0.0141^{**}		
$\times$ $Fraction_{GW}$		-0.0143		
$\times$ $Fraction_{Inv}$		-0.0502		
$\times$ $Fraction_{Div}$		-0.0316		
Int Scope 1			-0.0084	
$\times$ $Fraction_{GW}$			0.0445	
$\times$ $Fraction_{Inv}$			-0.0535	
$\times$ $Fraction_{Div}$			-0.2797^{**}	
I(Green Loan)				-0.2548^{***}
$\times$ $Fraction_{GW}$				-0.0048
$\times$ $Fraction_{Inv}$				0.6092^{*}
$\times$ $Fraction_{Div}$				-0.4484
Firm-level Controls	Y	Y	Y	Y
Rating FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	3,654	3,277	3,277	3,654
R^2_{adj}	0.329	0.329	0.329	0.334

Appendix for Financed Emissions

A.1. Firm-level Data

In this section, we provide additional details for the construction of our firm-level outcome variables. Table A.1 provides the definitions of these variables.

In order to maximize the number of observations in our analysis, we supplement Compustat North America and Compustat Global with data on firm fundamentals from Worldscope. From these three data sources, we choose a single data source for each firm in order to maximize the number of non-missing firm-year observations for that firm. We source data on firm fundamentals from Compustat North America for roughly 47 percent of our firms, from Compustat Global for roughly 38 percent of our firms, and Worldscope for roughly 15 percent of our firms. We choose a single data source in order to avoid introducing measurement error within a given firm's time series of observations related to changing data sources. We also note that our analysis of firm-level outcomes include firm fixed effects and cluster standard errors at the firm-level, such that systematic differences across data sources should have minimal impact on our analysis.

Where possible, we follow Tobek and Hronec (2018) to map Worldscope variables to their Compustat counterparts. Table A.2 provides this mapping between variable names, as well as Pearson and Spearman correlations between Compustat North America and Worldscope variables for firms that have non-missing data from both sources over the period 2010 to 2023.

We also supplement firm-level emissions data from Trucost with emissions data from LSEG (formerly Refinitiv Asset4). For firms with emissions data from LSEG but not Trucost, we calculate a fitted value for log emissions using coefficients estimated from firms with emissions data available from both sources. For Scope 1 absolute (intensity) emissions, the R^2 of the regression of log emissions from Trucost on log emissions from Refinitiv is 0.886 (0.847). For Scope 2 absolute (intensity) emissions, the R^2 of the regression of log emissions from Trucost on log emissions from Refinitiv is 0.837 (0.742). Results with firm-level emissions as the dependent variable are quantitatively similar if we only use data from Trucost or if we control for the data source in the regression using a binary variable equal to one if the observation is imputed from LSEG data.

A.2. Weighted Least Squares Results

In Section 4.4, we explore the impact of emissions targets on bank lending practices to targeted industries via OLS regressions. Given that this setting gives equal weight to industries both within and across banks, regardless of the relative deal volume in each bank-industry, we revisit these results within the context of weighted least squares (WLS) regressions in this section. Intuitively, these results should better capture the effects of emissions targets on aggregate lending.

Table A.3 provides WLS estimates akin to the specifications in Table 5, where observations are given weight proportional to the deal volume originated in an industry by a bank over the pre-period from 2015 to 2018 instead of equally weighting observations. Results are broadly consistent between the OLS and WLS regressions. In both cases, investor and divester banks reduce the number of deals they originate in targeted industries (Specification 4 of Panel A). Point estimates are larger in absolute terms for the WLS regressions indicating that the reduction in deal count is relatively larger in larger industries (as measured by pre-period deal volume). Turning to the impact of emissions targets on deal volume originated, we see that divester banks reduce deal volume in addition to reducing deal count. As with the OLS estimates, the relative reduction in deal volume is more pronounced in institutional deal volume than in pro-rata deal volume. Investor banks, on the other hand, tend to become more selective in their lending by reducing deal counts without reducing overall deal volume. In other words, we do not observe a statistically significant change in deal volume originated, although institutional deal volume falls in the WLS results.

A.3. 2SLS Results Using Distance-based Instrument

The 2SLS results in the main text follow the extant banking literature in using prior banking relationships as an instrument for current lender makeup. While these long lag instruments do create a notion of temporal separation between the the factors influencing the past decision and the current conditions, they do not fully account for the endogeneity of prior lending decision. In this section, we propose an alternative instrument, based on the distance between a firm's headquarters and the bank's headquarters, to provide additional evidence of the impact of loans from banks with emissions targets on firm outcomes.

As before, our instrument is the exposure of firm i to lenders of a given type with an emissions target in the firm's industry. Specifically,

$$Exposure_{GW,i,t} = \sum_j \omega_{i,j} \cdot hasTgt_{i,j,t} \cdot I(Type_j = \text{“}Greenwasher\text{”}) \tag{A.1}$$

where firm i's exposure to greenwasher banks at time t is a function of: a weight, $\omega_{i,j}$, specific to a firm-bank pair; a binary variable, $hasTgt_{i,j,t}$, equal to one if bank j has an emissions target in firm i's industry at time t, and zero otherwise; and a indicator variable, $I(Type_j = \text{“}Greenwasher\text{”})$, capturing whether bank j is of the type "Greenwasher". We define $Exposure_{Inv,i,t}$ and $Exposure_{Div,i,t}$ similarly by replacing the logical test of the bank's type with the appropriate type: $I(Type_j = \text{“}Investor\text{”})$ and $I(Type_j = \text{“}Divester\text{”})$, respectively.

In this setting, we replace the set of weights, $\omega_{i,j}$, based on prior lending relationships with a set of weights based on the distance between the headquarters of firm i and bank j. In contrast to papers such as Giroud, Liu, and Mueller (2024) that model exposure as a binary variable based on rings around a given location, we follow the spatial economics literature and allow the influence of bank j on firm i to decay exponentially with the distance between the two headquarters

$$\omega_{i,j} = \exp(-k \cdot Distance_{i,j}). \tag{A.2}$$

$Distance_{i,j}$ is the great-circle distance between the headquarters of firm i and bank j in miles, and the parameter k is chosen in a data-driven manner to maximize the fit of the first-stage following Abadie, Gu, and Shen (2024).[1]

Table A.4 presents the results of the first stage regressions of the $TgtLoan$ variables on the distance-based $Exposure$ variables defined above. In each case, the $Exposure$ variable is positively and significantly related to the corresponding $TgtLoan$ variable – e.g., $Exposure_{GW}$ is positively and significantly related to $TgtLoan_{GW}$. These relationships persist after controlling for the other $Exposure$ variables as in the even-numbered specifications. In short, firms tend to borrow more from banks that are located geographically closer to them, and this relationship is relatively strong with first-stage F statistics well above standard rules of thumb or the critical values of Stock and Yogo (2005).

Second-stage results in Table A.5 are consistent with the results in Table 9 of the main text. In Panel A, we see that firms that borrow from divester banks increase their cash holdings consistent with a precautionary savings motive. A firm going from having no bank debt provided by divester banks to having all of their bank debt provided by divester banks increases their cash holdings by roughly 11 percent. In this specification, we also observe a corresponding decrease in firm leverage, by rouhgly 14 percent, although this decrease is

[1] Specifically, we chose k to maximize the sum of the R^2 values across three regressions: 1) the regression of $TgtLoan_{GW}$ on $Exposure_{GW}$, 2) the regression of $TgtLoan_{Inv}$ on $Exposure_{Inv}$, and 3) the regression of $TgtLoan_{Div}$ on $Exposure_{Div}$. The value of k that maximizes the first stage is $4.53e-4$, which results in R^2 values of 0.243, 0.289, and 0.167. For simplicity, we omit the fixed effects to determine k. We obtain quantitatively similar 2SLS results if we include firm and industry-year fixed effects to determine k. Similarly, we obtain quantitatively similar 2SLS results and first-stage fit statistics using either a power decay function or beta distributed lags instead of an exponential decay function. Ghysels, Sinko, and Valkanov (2007) argue that beta distributed lags provide more flexibility with a single parameter; although their application is in the time domain rather than the distance domain. In the case of beta distributed lags, we transform the domain of distances to lie on the unit interval by scaling each distance by half the circumference of the earth.

not statistically significant in the 2SLS results in the main text.

Turning to the real outcomes in Panel B, we again see that firms that borrow from divester banks reduce their tangible assets in place by roughly 22 percent when going from having no bank debt supplied by divester banks to having all of their bank debt supplied by divester banks. Return on assets increases by roughly 63 percent for a similar change in bank debt supplied by greenwasher banks. Finally, we see the effects of loans from banks with emissions targets on firm emissions. Firms dealing with investor banks cut their emissions intensity by similar magnitudes as the results in the main text. In this setting, we also observe a decrease in both emissions intensity and absolute emissions for firms dealing with divester banks. This evidence is consistent with firms cutting tangible assets that are relatively brown rather than assets that are relatively less profitable in that we see return on assets fall for these firms.

Table A.1: Firm-level Variable Definitions

This table provides the definitions of firm-level variables used in this paper.

Variable	Definition	Source	Notes
Leverage	$\frac{DLTT+DLC}{AT}$	Compustat	This variable is winsorized at the 2.5% tails in each year.
Bank Debt	$TOTBANKDBTPCT/100$	Capital IQ	
Avail Credit	$\frac{TOTUNDRAWNCREDIT}{TOTUNDRAWNCREDIT+TOTBANKDBT}$	Capital IQ	
Cash	$\frac{CHE}{AT}$	Compustat	This variable is winsorized at the 1% tails in each year.
Int Exp	$\frac{XINT_t}{.5(DLTT_t+DLC_t+DLTT_{t-1}+DLC_{t-1})}$	Compustat	This variable is winsorized at the 2.5% tails in each year.
Assets	$\ln(1+AT)$	Compustat	
PP&E	$\frac{PPENT}{AT}$	Compustat	
Capex	$\frac{CAPX_t}{AT_{t-1}}$	Compustat	This variable is winsorized at the 1% tails in each year.
R&D	$\frac{XRD_t}{AT_{t-1}}$	Compustat	We set *XRD* equal to zero if it is negative or missing. This variable is winsorized at the 1% tails in each year.
ROA	$\frac{OIBDP_t}{.5(AT_t+AT_{t-1})}$	Compustat	We set *OIBDP* equal to the first non-missing value of $SALE-XOPR$ and $REVT-XOPR$ in cases where *OIBDP* is missing. This variable is winsorized at the 1% tails in each year.
Abs Scope 1	$\ln(DI\_319413)$	Trucost	*DI_319413* is GHG Scope 1 emissions in absolute terms.
Int Scope 1	$\ln(DI\_319407)$	Trucost	*DI_319407* is GHG Scope 1 emissions intensity (e.g., absolute emissions per $ revenue).

Table A.2: Firm-level Variable Definitions

This table provides a mapping between the variable names in Compustat and Worldscope. Where possible, we follow the mapping in Tobek and Hronec (2018). Pearson and Spearman correlations are calculated between Compustat North America and Worldscope for the period 2010 to 2023.

Compustat Variable	Worldscope Item	Pearson Correlation	Spearman Correlation
at	2999	0.998	0.999
dltt	3251	0.938	0.991
dlc	3051	0.884	0.905
che	2001	0.858	0.986
xint	1251	0.898	0.989
ppent	2501	0.997	0.967
capx	4601	0.994	0.865
xrd	1201	0.992	0.983
oibdp	1250 + 1151	0.920	0.974

Table A.3: Bank Classifications and Bank Lending - WLS

This table reports weighted least squares estimates for the impact of financed emissions targets on bank lending by bank type. The panel consists of bank-industry-year observations for the period 2015 to 2023. Industries are defined at the two-digit SIC code level. *I(# Deals > 0)* is a binary variable equal to one if the bank originates a loan in the industry during the year of the observation, and zero otherwise. Other indicator variables, denoted $I(\cdot)$, are similarly defined. $Targeted_{GW}$ is a binary variable equal to one if the bank is classified as a "Greenwasher" and has a financed emissions target for the industry at any point during the year of the observation, and zero otherwise. $Targeted_{Inv}$ and $Targeted_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. For an observation to be included in Panel B, the bank must have originated at least one loan in the given industry in the given year. Observation weights are proportional to the loan volume in 2020 dollars originated by a bank in an industry over the period 2015 to 2018. Standard errors are clustered at the bank-industry level. Fixed effects are included to control for bank-industry and industry-year. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Propensity to Lend and Amount of Lending

	I(# Deals > 0)	I($ ProRata > 0)	I($ Inst > 0)	ln(1+ # Deals)	ln(1+ $ Deals)	ln(1+ $ ProRata)	ln(1+ $ Inst)
$Targeted_{GW}$	−0.0141	0.0212	0.0181	−0.0847	−0.1500	0.0408	−0.0963
	(0.0431)	(0.0446)	(0.0315)	(0.0625)	(0.2398)	(0.2553)	(0.1814)
$Targeted_{Inv}$	0.0076	0.0219	−0.0663	−0.2263***	−0.1702	−0.1268	−0.3887*
	(0.0288)	(0.0288)	(0.0434)	(0.0469)	(0.1812)	(0.1651)	(0.2246)
$Targeted_{Div}$	−0.0266	−0.0450	−0.0747*	−0.2234***	−0.3524**	−0.3753**	−0.4977***
	(0.0350)	(0.0362)	(0.0382)	(0.0420)	(0.1683)	(0.1767)	(0.1772)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y
N	67,600	67,600	67,600	67,600	67,600	67,600	67,600
R^2_{adj}	0.663	0.635	0.585	0.866	0.753	0.733	0.655

Panel B: Average Deal Size and Loan Characteristics

	ln($ Deals)	ln($ ProRata)	ln($ Inst)	Pro Rata Share	ln(Maturity)	ln(All in Spread)
$Targeted_{GW}$	−0.0658	−0.0378	−0.0766	0.0309	−0.0076	−0.0833
	(0.0520)	(0.0594)	(0.0833)	(0.0274)	(0.0319)	(0.0596)
$Targeted_{Inv}$	0.0206	−0.0424	0.2057*	0.0055	−0.0057	−0.0055
	(0.0759)	(0.0942)	(0.1065)	(0.0300)	(0.0448)	(0.0510)
$Targeted_{Div}$	0.0069	−0.0622	−0.1322	0.0136	−0.0120	0.0979
	(0.0649)	(0.0961)	(0.1060)	(0.0394)	(0.0386)	(0.0797)
Bank-SIC2 FEs	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y
N	19,880	17,534	14,076	19,880	19,783	14,621
R^2_{adj}	0.423	0.368	0.344	0.182	0.239	0.286

Table A.4: Financed Emissions Targets and Firm Outcomes – First Stage

This table reports the estimates for the impact of a relationship with a bank with a financed emissions target on the fraction of a firm's bank debt originated by a bank with a financed emissions target. The panel consists of firm-year observations for the period 2015 to 2023. The dependent variable in the first two specifications is $TgtLoan_{GW}$ equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank that has a financed emissions target in the firm's industry. $TgtLoan_{Inv}$ and $TgtLoan_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. $Exposure_{GW}$ is equal to the fraction of banks classified as a "Greenwasher" weighted by the distance between the firm's headquarters and the bank's headquarters. $Exposure_{Inv}$ and $Exposure_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Industries are defined at the two-digit SIC code level. Standard errors are clustered at the firm level. Fixed effects are included at the firm- and industry-year-level. First stage F-statistics for the 2SLS regression of log assets on the *TgtLoan* variables are reported. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	TgtLoan_{GW}		TgtLoan_{Inv}		TgtLoan_{Div}	
	(1)	(2)	(3)	(4)	(5)	(6)
$Exposure_{GW}$	0.2748***	0.2831***		−0.0091		−0.0164
	(0.0709)	(0.0780)		(0.0896)		(0.0513)
$Exposure_{Inv}$		−0.0088	0.5843***	0.6184***		−0.1230**
		(0.0657)	(0.0758)	(0.0894)		(0.0554)
$Exposure_{Div}$		0.0462		−0.1325**	0.5243***	0.5375***
		(0.0495)		(0.0522)	(0.0578)	(0.0583)
Firm FEs	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y
N	59,041	59,041	59,041	59,041	59,041	59,041
R^2_{adj}	0.334	0.334	0.415	0.416	0.337	0.338
First Stage F-stat	434.2	151.4	1,379.5	505.8	4,015.2	1,382.6

Table A.5: Financed Emissions Targets and Firm Outcomes – 2SLS

This table reports the two-stage least squares (2SLS) estimates for the impact of financed emissions targets on firm outcomes. The panel consists of firm-year observations for the period 2015 to 2023. The dependent variables are defined in Table A.1. $TgtLoan_{GW}$ equal to the fraction of the firm's bank debt originated by a "Greenwasher" bank that has a financed emissions target in the firm's industry. $TgtLoan_{Inv}$ and $TgtLoan_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. We instrument for these endogenous variables with a set of exposure variables based on relationship lending between the banks in our sample and the panel of firms. $Exposure_{GW}$ is equal to the fraction of banks classified as a "Greenwasher" weighted by the distance between the firm's headquarters and the bank's headquarters. $Exposure_{Inv}$ and $Exposure_{Div}$ are defined similarly for "Investor" and "Divester" banks, respectively. Industries are defined at the two-digit SIC code level. Standard errors are clustered at the firm level. Fixed effects are included at the firm- and industry-year-level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Financial Outcomes

	Leverage	Bank Debt	Avail Credit	Cash	Int Exp
$TgtLoan_{GW}$	0.2295	0.5836	−0.2798	0.1746*	0.0449
	(0.1676)	(0.4079)	(0.4673)	(0.1053)	(0.0329)
$TgtLoan_{Inv}$	0.0745	0.2812	−0.1868	−0.0359	−0.0004
	(0.0801)	(0.2229)	(0.2118)	(0.0491)	(0.0148)
$TgtLoan_{Div}$	−0.1432*	0.1881	−0.1784	0.1166**	−0.0088
	(0.0812)	(0.1687)	(0.1750)	(0.0526)	(0.0130)
Firm FEs	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y
N	58,794	56,629	49,445	58,077	55,183
R^2_{adj}	0.798	0.674	0.762	0.774	0.700
First Stage F-stats:					
$TgtLoan_{GW}$	153.6	150.1	104.6	149.2	127.3
$TgtLoan_{Inv}$	510.4	482.9	422.3	497.9	464.4
$TgtLoan_{Div}$	1,373.3	1,435.0	1,494.2	1,361.0	1,380.1

Table A.5: Financed Emissions Targets and Firm Outcomes – 2SLS (cont.)

Panel B: Real Outcomes

	Assets	PP&E	Capex	R&D	ROA	Abs Scope 1	Int Scope 1
$TgtLoan_{GW}$	-0.1673	0.1326	0.1616**	-0.0034	0.6382***	1.9367	0.8434
	(0.6633)	(0.1474)	(0.0779)	(0.0076)	(0.2020)	(2.0703)	(1.8902)
$TgtLoan_{Inv}$	0.8677***	-0.1139*	-0.0777**	-0.0036	-0.1241	-1.2427	-2.0641*
	(0.3034)	(0.0689)	(0.0378)	(0.0043)	(0.0895)	(1.2773)	(1.1671)
$TgtLoan_{Div}$	-0.1134	-0.2189***	0.0167	-0.0086**	-0.1704**	-2.0674**	-1.9989**
	(0.3357)	(0.0827)	(0.0304)	(0.0041)	(0.0857)	(0.9671)	(0.9154)
Firm FEs	Y	Y	Y	Y	Y	Y	Y
SIC2-Year FEs	Y	Y	Y	Y	Y	Y	Y
N	59,041	57,692	57,570	58,282	58,157	40,790	40,785
R^2_{adj}	0.971	0.943	0.581	0.922	0.620	0.941	0.925
First Stage F-stats:							
$TgtLoan_{GW}$	151.4	148.6	158.3	142.6	141.5	160.1	161.1
$TgtLoan_{Inv}$	505.8	497.9	490.0	497.4	495.0	318.8	319.0
$TgtLoan_{Div}$	1,382.6	1,357.5	1,380.8	1,378.3	1,386.7	1,254.4	1,261.2