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ABSTRACT

In the past two decades, several banks have joined global initiatives aimed at enhancing the disclosure of their asset portfolios and climate commitments. We study whether banks that joined such initiatives have altered the emission exposure of their syndicated loan portfolios. We rely on loan-level data with global coverage combined with country-industry data on emissions. We find that, on average, banks have reduced the emission exposures of their syndicated loan portfolios over the last decade. However, we do not find statistically significant or robust differences between banks that did and those that did not subscribe to climate commitments. In the few instances where we found a statistically significant change after becoming a climate initiative signatory, the effect was either temporary or did not survive our robustness testing. Thus, we conclude that while banks reduced their relative lending to highly-emitting sectors on average, voluntary climate commitments did not contribute to syndicated loan reallocation away from those sectors.

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1 Introduction

In 2006, Kofi Annan launched the United Nations initiative of Principles for Responsible Investment (PRI) designed to draw the attention of financial institutions to sustainable development goals, including climate sustainability. It was not until 2015, however, with Mark Carney's speech on the "tragedy of the horizon" that financial regulators started to include climate-related risks into their discussions of financial stability. The establishment of the Task Force on Climate-related Financial Disclosure (TCFD) by the Financial Stability Board, then chaired by Carney, followed suit. Finally, in 2019, the Principles for Responsible Banking (PRB) were launched. The idea behind these efforts is that enhancing the disclosure of financial institutions' balance sheets would allow for shareholders and stakeholders to better make assessments about financial institutions' carbon footprints and their exposures and commitments to climate-related risks. This enhanced accountability could also lead financial institutions to move their investments away from high-emission sectors, therefore "greening" their portfolio and disincentivizing investment into technologies with high emissions. The literature, however, has provided evidence that this strategy would not necessarily reduce emissions, as some firms could reduce investments in greening their technologies in face of higher cost of borrowing (*e.g.*, Hartzmark and Shue, 2022; Ye, 2023).

Following the launch of each of these initiatives, many banks have signed the PRI, TCFD, and/or PRB agreements. These agreements require banks to measure and report greenhouse gas emissions embedded in their asset portfolios, while PRI and PRB also include specific limits on such exposures. We assess whether financial institutions have changed the sectoral allocation of their global syndicated lending after signing these initiatives. That is, we take a broad view on the question and ask whether there is any evidence that voluntary green commitments made by banks lead to a reduction of credit to highly-emitting *industries*. Have the institutions that subscribed to any (or more than one) of these initiatives reallocated their loans to lower-emitting sectors? Have they materially divested from higher-emission sectors? Have they altered the characteristics of loans to borrowers in higher-emitting industries? We analyze these questions for the universe of syndicated bank loans originated by the largest players in that market between 2015 and 2022.

Recent empirical literature has made some progress in assessing the effect of portfolio greening initiatives on financial capital allocation. Looking at bank-firm pairs, Kacperczyk and Peydró (2022) find that banks that have made climate commitments reallocated their funding from firms with high to firms with low direct emissions (Scope 1). These findings are corroborated by the analysis in Reghezza et al. (2022) and Mueller and Sfrappini (2022) which find that European banks reduced their lending to European companies with high emissions after the Paris Accord in 2015. Since low-emission firms could be in industries that do not innovate in green technologies, these dynamics can be counterproductive to climate goals. In fact, Kacperczyk and Peydró (2022) show that high-emission firms reduce their investments and do not improve their emission efficiency when their funding is reduced. Similarly, Ye (2023) show that high-emission firms obtain fewer green patents when their relationship banks make climate commitments. There is also evidence that climate risks, commonly proxied by firms' emissions, are reflected in loan pricing (Degryse et al., 2023; Ehlers et al., 2022; Hrazdil et al., 2020), although the evidence is mixed on whether there is a difference between banks that made climate commitments and banks that did not. Unlike this literature, we focus on industries rather than firms in our analysis. While this is so mostly due to data limitations, it comes with the advantage of avoiding self-reported firm data on emissions, which could provide more granularity but also suffer from possible selection bias, imprecision, inaccuracy, and "greenwashing" (Bingler et al., 2024; Crippa et al., 2025; Greenstone et al., 2023).

Our analysis does not aim to contribute to the discussion on whether banks' behavior leads to a smaller or larger investment by industries in greener technologies. Our focus, instead, is solely on financial institutions' behavior in response to their own commitments. Our goal is to take the broadest view possible on the question of how green commitments might have affected the global industry composition of bank lending. To do so, we focus on the syndicated loan market, for which global bank lending information is available at the loan level. For each loan, we reallocate the lender information to each lender's global ultimate owner (GUO), as climate commitments are made at the headquarter level. We focus on 59 GUOs, which account for nearly 40% of syndicated loans extended globally during our sample period. Given our focus on the industrial composition of bank lending, we rely on the World Input-Output Database (WIOD) environmental accounts to measure country-industry emissions. We match each borrower to their corresponding country and industry, and assign an emission metric to each loan. We conduct our analysis both at the bank and at the loan levels. The former allows us to measure dynamics over time, while the latter focuses on a static analysis. Since most findings in the literature point to changes in bank behavior only occurring after the Paris Accord and Mark Carney's speech,[1] we limit our sample to the 2015-2022 period.

We address the industrial composition of loan portfolios in two ways — first by looking at the average effect of signing commitments on the emission exposure of banks' syndicated loan portfolios and the emission intensity of the borrowers, and then by testing whether banks that signed a commitment started originating fewer loans to firms that are at the right tail of the emission intensity distribution. We find that all banks, regardless of whether they made any climate commitments, reduced their lending to highly-emitting sectors during our sample period. However, signing climate commitments is not associated with significant differences in syndicated loan allocations. We find this null result in a variety of alternative measures of emissions exposure (*e.g.,* ESG scores), estimation methods (*e.g.*, quantile regressions), sets of controls, subsample splits (*e.g.*, top emitters borrowing), and empirical specifications (*e.g.*, alternative residual clustering).

Another possible margin of adjustment by banks could be through changes in the maturity structure of their loans. One way to reduce exposure of the loan portfolio to higher-emitting sectors is to shorten the maturities of loans extended to firms in these sectors.[2] Thus, we test whether banks change the maturity of their loans once they become signatories of climate commitments.

[1] *E.g.*, Delis et al. (2018), Ehlers et al. (2022), and Reghezza et al. (2022) provide evidence on changes in bank behavior following the 2015 Paris Accord.

[2] Using firm-level data, Ivanov et al. (2023) find that higher-emitting firms face shorter loan maturities.

Once again, however, we were not able to find robust changes in lending practices of banks after they signed climate agreements.

Our paper contributes to the strand of literature that studies syndicated loans and climate-related questions. Previous work has focused on the degree to which climate risk is priced in loans (Hrazdil et al., 2020; Ehlers et al., 2022; Mueller and Sfrappini, 2022; Degryse et al., 2023). Although there is evidence of a "carbon premium" in loans since the Paris Agreement of 2015, the effect of climate regulatory risk depends on several factors, including firms' exposure and location (Mueller and Sfrappini, 2022). Moreover, "green" banks, both *de facto* and as signaled through climate agreements, do not seem to price carbon differently than non-green banks across all firms, although they do price it differently across "green" firms (Ehlers et al., 2022; Degryse et al., 2023). In addition, Ho and Wong (2023) find that climate transition risks have been increasingly priced into syndicated loans to emissions-intensive sectors in emerging markets after the signing of the Paris agreement. In terms of loan composition, Martini et al. (2025) find that U.S. banks reduced their exposure to high emitters by lending more to low emitters while Bruno and Lombini (2023) find a non-linear relationship between borrowers' CO2 emissions and syndicated bank lending, but they do not analyze the effects of climate commitments.

Our work is also related to the broader literature on climate risk in financial markets. Work on equity returns has shown evidence of a "greenium," or an asset risk premium, associated with the greenness and transparency factor that is priced into investments, although this premium may be muted during the transition period (Alessi et al., 2021; Zhang, 2023). This carbon premium is present for firms all over the world, with higher short-term premiums in developed countries, and is found to depend on both the level and (percent) changes in emissions (Bolton and Kacperczyk, 2023). Similarly, the literature on carbon pricing on bond markets shows that corporate and municipal bonds are priced with a climate risk premium, affecting both bond credit ratings and yield spreads (Baker et al., 2022; Acharya et al., 2022; Seltzer et al., 2022; Goldsmith-Pinkham et al., 2023). Finally, the literature has also explored the relationship between sovereign debt and physical climate risk and found that natural disasters and anomalies can increase the risk of default and impact governments' borrowing conditions (Mallucci, 2022; Diarra and Jaber, 2022; Phan and Schwartzman, 2023).

Since we do not find substantial divestment from high-emitting industries among banks that made climate commitments, and the evidence of decline in maturities of loans to firms in these industries is limited and not robust, we conclude that there is no material behavioral change in response to these initiatives, at least with respect to industrial composition of syndicated loan portfolios.[3] Of course, a natural follow up question to our analysis is whether banks implement other principles outlined in PRI and PRB that require direct influence over the green activities of borrowers (Morse and Sastry, 2024). This has recently been addressed in papers documenting the effect of climate agreements on banks and borrowers' practices. Hasan et al. (2026) identify

[3] A very similar result is found in a contemporaneous study by Giannetti et al. (2024) using credit registry data for the EU.

an improved environmental performance among client firms of TCFD-member lenders relative to control firms. Similarly, Houston and Shan (2021) show that lenders' Environmental, Social, and Governance (ESG) scores can influence borrowers' ESG scores. The limitation of our data with industry-level emissions is that we cannot observe whether banks reallocate their loans to greener firms within a given sector, but the literature has found evidence of some within-industry reallocation.[4] Moreover, an interesting question for future research is whether borrowers are greening their technologies more if their relationship banks make green commitments.

We begin by describing details of the different voluntary commitments in Section 2. Section 3 describes the data. We report our main empirical approach in Section 4, our main findings in Section 5, and robustness tests in Section 6. The last section concludes.

2 Institutional context

Our analysis focuses on three climate commitments designed to support climate-related financial disclosures and promote sustainable frameworks for banking and investing. The first of these commitments is the United Nations' Principles for Responsible Investment (PRI). Established in 2006 with just over 70 signatories, the PRI promotes the incorporation of Environmental, Social, and Corporate Governance (ESG) responsibility factors into investment decisions. As of 2021, there were nearly 4,000 total signatories and over 700 asset owner signatories that regularly provide PRI-outlined disclosures. PRI signatories commit to the adoption and implementation of six main principles. According to the principles, ESG issues are to be incorporated into investment analysis and decision-making processes. They are also to be incorporated into ownership policies and practices. Signatories are expected to seek disclosure from the entities in which they invest. They should promote acceptance and implementation of the principles within the investment industry, and work together to enhance the effectiveness of the principle implementation. Lastly, signatories are expected to report activities and their progress towards the principles' implementation.

Similarly, United Nations' Principles for Responsible Banking (PRB) was created in 2019 to provide a framework for sustainable finance alignment and disclosure in accordance with the United Nations' Sustainable Development Goals and the 2015 Paris Climate Agreement. In 2024, there were more than 300 signatories covering approximately fifty percent of global assets. PRB signatories commit to the adoption and implementation of six principles, which are meant to align business strategy to frameworks such as the Sustainable Development Goals, the Paris Climate Agreement, and other national/regional goals. Targets are to be set and published with the aim of continuously

[4] For example, Polo et al. (2024) show that banks charge higher interest rates to higher-emitting firms, with banks that have publicly committed to decarbonization efforts charging higher climate risk premiums. Ding et al. (2023) find that firms with higher emissions receive fewer new bank loans and see reduced term structures in those that they do receive. Ye (2023) show that bank divestment from high-emission firms stifles green innovation among these firms, while promoting green innovation among lower-emission firms that subsequently receive increased lending from these banks. Newton et al. (2022) show how ESG ratings mediate lender-borrower matching, with higher ESG-rated banks being more likely to give loans to higher ESG-rated firms.

increasing positive impact and reducing negative impact on, and managing risk to, people and the environment. Signatories are to work with clients and customers to encourage sustainable practices and activities and consult with relevant stakeholders to achieve societal sustainability goals. The principles are to be implemented through effective governance and responsible banking. Lastly, signatories are to be transparent and accountable about performance.

In 2015, the Financial Stability Board established the Task Force on Climate-related Financial Disclosure (TCFD). It is designed to provide recommendations for voluntary climate-related disclosures that are comparable and widely adoptable across sectors. With more than 4,000 supporters, the TCFD established eleven main recommendations aimed to increase climate-related financial risk exposure transparency in four areas: governance, strategy, risk management, and metrics and targets. For governance, it recommends that organizations disclose their oversight and the roles of boards and management in assessing and managing climate-related risks and opportunities. For strategy, it recommends that organizations disclose the actual and potential impacts of climate-related matters. This includes describing the risks and opportunities identified over short, medium, and long terms, as well as the impact on businesses, strategy, and financial planning. Such strategy should include a description of resilience to different climate-related scenarios. For risk management, it recommends that organizations disclose how climate-related risks are identified, assessed, and managed. Disclosures include specific processes and how these processes are integrated into overall risk management. For metrics and targets, it recommends that organizations report scope 1, 2, and 3 greenhouse gas emissions, if appropriate, and their performance against targets, in line with their strategy and risk management processes. In October 2023, the TCFD released its last report and passed on climate-related disclosure monitoring to the International Financial Reporting Standards Foundation.

Despite their differences, all three voluntary commitments, PRI, PRB, and TCFD, are intended to provide incentives to financial institutions to measure, report, and potentially reduce the exposure of their loan portfolio to emissions produced by their borrowers. In contrast with PRI and PRB, which impose a limit on climate exposure of the asset side of the balance sheet of member firms, TCFD only requires disclosure. That said, in our benchmark analysis, we do not assume that all three types of commitments will have the same effects, and conduct our analysis separately for each commitment type.

The emissions exposure of loan portfolios can be reduced in a variety of ways. For example, exposure can be reduced through engagement with borrowers and incentives for existing borrowers to reduce their emissions, or through a reallocation of loans to firms that have lower emissions or that are actively reducing their emissions within a given industry, or through a divestment from high-emitting industries.[5] While all approaches are consistent with the goal of reducing borrowers' emissions, our analysis is designed to capture the third one. We also note that this third approach has the potential of being at odds with climate goals, by depriving industries that have high

[5]In a recent study for the case of Brazil, Miguel et al. (2024) find that disclosure regulations led to reallocation of bank credit away from high-emitting firms.

emissions from much needed funding for investment in green technologies.

3 Data Sources and Patterns

Our data come from three main sources: The LSEG Loan Connector DealScan database of syndicated loans, which is available at the loan level and provides information on loan characteristics, the composition of loan syndicate, and limited information about borrowers; the World Input-Output Database (WIOD) which in its environmental accounts provides emissions by country-industry pair; and online resources for banks' climate commitments.

3.1 Banks' commitments

For each climate initiative we focus on (TCFD, PRI, and PRB), we obtain a list of each participating bank's signing month and year from the official agreement websites. We merge these signatory records into our loan sample at the bank-date level. Because bank names can be written differently across databases, we use a manual string-matching process to ensure that bank names defined in our loan sample are appropriately attributed to corresponding signatories. The Appendix Table A1 reports the signing dates by agreement for all banks in our sample. Table A2 shows loan characteristics for each of the banks in our sample, separating banks that signed at least one commitment from those that never signed any commitments.

In our robustness tests, we also use data on banks' climate commitment ratings from the LSEG ESG Score database, which provides an Environmental Pillar Score (E-score) time series for most banks in our sample. The E-score measures institution's resource use, emissions, and innovation performance relative to other companies. This ranking process is calculated using the industry group as the benchmark. For each bank, we use E-scores for every available year, which varies by bank. In addition, we collect data on banks adherence to Equator Principles and banks making Net Zero commitments, also as alternative measures of green commitments that we use in our robustness tests.

3.2 Syndicated loans

We use data on syndicated loans from LSEG Loan Connector DealScan dataset. This dataset contains comprehensive information on the universe of all loans from the global syndicated loan market as contained in DealScan. We pull all loans available in the DealScan data set from January 2015 to November 2022. The raw data set contains 685,465 loan-level observations. Importantly, the information pertains only to loan origination and does not include data on sales of loan shares that may occur subsequently. Thus, our study is about banks' decisions to participate in lending to specific sectors, which is where the effect of commitments is likely to be most apparent.

Since climate commitments are made at the corporate level, we assign loans issued by affiliates to the global ultimate owner level relying on bank names matched with the global ultimate owner (GUO) name. If affiliates of the GUO participate in the same syndicate, we simply add their shares up. For our benchmark analysis, we include all syndicate participants, as we are testing the impact of climate-related commitments on the decisions to be involved in lending to highly-emitting sectors. While the syndicated loan arrangers decide on whether to initiate a loan contract, participating banks decide on whether to extend credit to the borrower. In our robustness tests, we also estimate the effects of climate commitments on lead arrangers' behavior, and find that the narrative for them is the same as for all participants.

We limit our sample in a few ways. First, we only include loans from the largest parent banks, which we define as those representing larger than 0.1 percent market share between 2010 and 2019. To calculate this share, we aggregate the total value of loan deals for each parent bank and construct their share of the total market. Second, we exclude government-owned banks from our sample. Third, we focus on loans extended between 2015 and 2022. This data filtering yields a sample of 387,643 loan-level observations. Lastly, we limit our sample to loans extended to borrowers that we can match to the emissions dataset. This implies that some loans are not included in our analysis because the borrowers do not yield a match, which is usually due to missing information on the industry of the borrower. Our final sample includes the 59 largest parent banks and 269,412 loan-level observations, corresponding to 39.3 percent of the total number of loans extended between 2015 and 2022. Table A1 provides a list of banks in this final sample. Borrowers in this sample represent 564 industry-country combinations and operate in 29 countries.

The unit of observation is a loan facility. While loan facilities may comprise multiple tranches, we conduct our analysis at the facility level. DealScan provides detailed information on each loan at origination. These details include size, maturity, and other contract details, including facility and deal amounts and active dates. For each observation, we also have information on the lender and borrower entities. We use this information to control for lender and borrower characteristics in our analysis. We match each borrower to the borrower's nationality of operations, which is where emissions are most likely to occur. Finally, we use the Standard Industrial Classification (SIC) classification of the borrower (from DealScan) to match the borrower's industry to the WIOD classification. We use this information to connect banks' loans to borrower emissions' measures.

As a balance test, we evaluate the industrial composition of loans extended by banks with and without climate commitments. Figure 1 plots the annual total dollar amount of loans (in logs) by major industry. The sample is split between banks that made at least one of the three commitments (PRI, TCFD or PRB) at some point in time versus those which never did. A comparison between panels (a) and (b) shows very little difference in the industrial composition of loans. It does not show, however, any major trend difference across the two groups.

3.3 Emissions measurement

We measure environmental performance for each bank by matching borrowers to country-industry Scope 1 emissions, which are defined as the greenhouse gas emissions created directly by sources owned and operated by a given organization. Our emissions data come from the WIOD 2016 Environmental Accounts Dataset. The original dataset provides information on total Scope 1 emissions and gross output for 32 countries. The dataset has different industry coverage for each country, covering a total of 49 different industries from 2005 to 2016. Country-industry coverage varies by year and is most complete for the last year in the data, 2014. Therefore, we use country-industry-level carbon dioxide emissions in 2014, which covers 32 countries and up to 49 industries. Emissions in 2014 are a good measure for country-industry's emissions exposure, as 99.7% of variance in emissions data is between country-industry pairs, and only 0.3% corresponds to variance over time. We scale these emissions by gross output of the given industry in a given country to account for differences in industry size. Hence, our final measure of country-industry emissions is a ratio of 2014 Scope 1 emissions to gross output, commonly known as emission intensity. This measure is applied to all loans received by borrowers within an industry-country pair, regardless of the year of the loan in our sample.

Because the distribution of the ratio of Scope 1 emissions to output is very skewed, even after scaling by gross output, it is hard to interpret differences across industries. Thus, we compute an overall distribution of percentiles of emissions from each country-industry pair, resulting in individual emission intensity values that are projected onto a 0-100 scale. In this distribution, high values of the resulting index correspond to high emissions.

To match our country-industry emissions measures, we rely on the fact that loans in our DealScan dataset have SIC industry codes. For our sample of loan facilities, we use each loan's 4-digit SIC industry code to match observations to our constructed measure of emissions. We drop borrowers in countries that do not report emissions in some industries. We are also unable to match all observations due to some missing SIC codes in the loan dataset. The Appendix Figure A1 reports the distribution of the emissions index in panel (a) and emissions to gross output ratios (emissions intensity) in panel (b).

Our analysis is conducted at the bank and loan levels. For the former, we construct an aggregated measure of the emission exposure of each banks' portfolio in a given year. To do so, we use a weighted average of the emissions index for all new loans each bank extended in a given year, using total loan facility amounts as weights. Participant shares are only available for about 13% of our sample, thus we do not try to divide facility amounts. In the robustness tests, we show that our results do not change if we equally divide facility amount across participants. Thus, we end up with a portfolio-aggregated measure of emission exposure for each bank in each year in our sample. As an alternative specification, we flag borrowers that are in the top 10 percent of emission intensity distribution across country-industry cells and test, at the loan level, whether climate commitments affect the probability of lending to borrowers in these high-emitting country-industry cells. Notably, 71.8% of total emissions are emmitted by country-industries in the top decile of emissions in our sample (emissions by decile are provided in the Online Appendix).

Given that our loan data is very detailed, one may ask why we do not use firm-level emissions data now available from a number of private data providers. Unfortunately, mandatory emissions reporting is currently limited to a very small number of countries, a limited set of industries, and is quite recent. The voluntary reporting on which data providers rely is only available for publicly traded firms. Moreover, these data are very limited in coverage, not audited, and are potentially subject to selection bias (Bingler et al., 2024; Greenstone et al., 2023). Since our interest is in the industrial composition of bank loans, a broad global coverage of country-industry emissions data suits our purposes better.

To document overall trend in intensity of emissions in syndicated bank lending by major players in the market, Figure 2 reports the average emission exposure across all loans by year, measured as the average log facility-amount-weighted total emissions by industries in our sample. Panel (a) reports the statistic for all banks, while panel (b) splits the sample between banks that signed at least one commitment (PRI, PRB, or TCFD) and those that never did. 48 out of the 59 banks in our sample signed multiple different commitments. The figure highlights a substantial decline in average exposure over time overall and for both groups of banks. In our estimates we will control for this downward trend by including year fixed effects. Because we observe that signatory banks have lower emissions exposure on average throughout the sample, we allow for bank fixed effects to isolate the effect of signing a commitment. As a result, most of our results are identified by within-bank variations in emissions exposure of the syndicated loan portfolios relative to common fluctuations.

3.4 Event study

To describe the raw-data patterns of the effects of climate commitments on emissions intensity of bank lending, we perform an event-study analysis.

Specifically, we estimate the effect of making a climate commitment at time t_0 on the Emission Index of its loans, at a quarterly frequency:

$$EI_{lbt} = \sum_{s=t_b^0-10}^{t_b^0+20} \beta_s + \alpha_t + \epsilon_{lbt}, \tag{1}$$

where EI_{lbt} is the emission index of loan l originated by bank b in quarter t, s is the index of quarterly leads and lags relative to the signing of a specific climate commitment by bank b in month t_b^0, α_t are year fixed effects to absorb any common trends.

To evaluate effects on loan maturity, we also estimate

$$MtM_{lbt} = \sum_{s=t_b^0-10}^{t_b^0+20} \beta_s + \mu\, EI_{lbt} + \sum_{s=t_b^0-10}^{t_b^0+20} \gamma_s\, EI_{lbs} + \alpha_t + \epsilon_{it}, \tag{2}$$

where MtM_{lbt} is the maturity (in months) of loan l originated by bank b in quarter t. The coefficients of interest are the γ's, since we want to assess if banks changed the maturity of their loans to high-emitting borrowers relative to low-emitting ones.

Figure 3 shows the effects of signing commitments on the emission index and on the maturity of loans to higher-emitting sectors. The top panels show a borderline significant decline in the emissions index following the commitment to PRI. The other commitments, TCFD and PRB, do not seem to have an effect on loans composition with respect to emissions, although there is a visible downward trend around signing of TCFD. The bottom panels show no statistically significant effect of signing a commitment to PRI, TCFD, or PRB on maturities of loans to high-emission borrowers relative to low-emission ones.

We next turn to a regression analysis to better understand these dynamics.

4 Empirical specifications

We consider estimates both at the bank and loan levels. Our bank-level regressions allow us to explore bank-lending practices over time which we do by estimating difference-in-differences local projections – "LP-DiDs" – (Dube et al., 2023; Jordà, 2005; Jordà and Taylor, 2025). Our loan-level estimates focus on loan origination and estimate average effects across the sample with alternative sets of controls. Because of the lack of panel structure in loan-level data, we cannot conduct a dynamic analysis similar to the bank-level one. The event study presented in Section 3.4 is the closest we can get to a dynamic setting using loan-level data.

For both bank- and loan-level estimates we consider the full sample, as well as estimates focusing on top emitters. The latter are important in our analysis because emissions are concentrated in a handful of sectors. We define high-emission industries as those that are in the top decile of the country-industry emission intensity distribution. We choose the top decile because of the highly skewed nature of this distribution. The industries that account for the highest share of total emissions in our sample are electricity and gas supply (67.5% of total emissions), coke and petroleum manufacturing (11.5% of total emissions), chemicals manufacturing (4.1% of total emissions), and land transportation (2.2% of total emissions).

Changing loan composition, however, is not the only way to act on climate-reduction commitments. Financial institutions could opt to diversify away from highly-emitting sectors over time and do so by potentially shortening the maturity of the loans extended to these sectors. Therefore, for both the bank- and loan-level analysis, we also assess the effects of climate commitments on the maturity structure of loans, conditional on the emissions intensity of the borrowers.

4.1 Bank lending over time

We assess the potential effects of climate commitments on banks' lending practices over time using difference-in-differences local projections (LPDiD), as introduced by Dube et al. (2023), Jordà (2005), and Jordà and Taylor (2025). Specifically, we estimate:

$$EE_{bt+h} - EE_{bt-1} = \alpha_t + \alpha_b + \beta_h(S_{bt} - S_{bt-1}) + \varepsilon_{bt}, \tag{3}$$

where EE_{bt} is the emission exposure of the portfolio of loans issued in year t with participation of bank b. This is computed as a weighted average of the emission index (EI_{lbt}) of all loans originated by syndicates with participation of bank b in year t using the loan amounts (converted to U.S. dollars at the spot rate at the time of loan origination) as weights. S_{bt} indicates whether bank b has signed a given climate commitment by year t. S_{bt} equals one in the year a bank signed a given commitment and in all future years. Otherwise, S_{bt} is set to zero if a bank has not signed a given commitment in year t or never signs that commitment. α_t is year-t fixed effect, and α_b is bank-b fixed effect. No other variables are included in the regressions, except as specified in our robustness exercises. We consider a horizon of up to 3 years, that is, $h \in \{0, \ldots, 3\}$.

The coefficients β_h, thus, reflect any change in the emissions exposure of bank b portfolio following its signing of commitment S, relative to banks that have not yet signed this commitment. If signing a commitment leads to banks reducing their emissions exposure, we expect $\beta_h < 0$.

We also estimate equation (3) while replacing the dependent variable with the share of loans extended to high-emission borrowers, defined as those in the top 10% of emission intensity distribution. Table A3 lists top industries in this group.

Finally, we estimate equation (3) replacing the emission exposure, EE_{bt+h}, with the difference between the average maturity of loans issued to high-emitters, that is, those at the top decile of the country-industry emissions intensity distribution, and those with median emissions.

4.2 Loan origination

We can also assess whether the characteristics of loans changed following the signature of one of commitments to PRI, TCFD or PRB. Unlike the bank-level regressions in which we can follow banks' lending practices over time, our loan-level regressions are static:

$$EI_{lbt} = \boldsymbol{\alpha} + \alpha_t + \beta_1 S_{bt} + \varepsilon_{lbt}, \tag{4}$$

where the dependent variable EI_{lbt} is the emission index of loan l with participation of bank b to borrower in country c in year t. S_{bt}, as defined before, equals one in the year a bank has signed a given commitment and every year thereafter. α_t is year-t fixed effect and $\boldsymbol{\alpha}$ corresponds to either a constant or a set of bank-b fixed effects or a set of bank-b and borrower's country-c fixed effects. The coefficient β_1 captures a change in the average emission index of bank b loans following the signing of a climate commitment. If green commitments lead banks to reduce loan origination to firms in highly-emitting industries, we expect $\beta_1 < 0$.

Alternatively, instead of measuring the effect of signing loan commitments on average emission index of the loans, we construct a "top emitter" indicator that equals 1 for loans to the borrowers in the top decile of country-industry emission intensity distribution, and 0 otherwise. We estimate:

$$I\,(\text{top } 10\%)_{lbt} = \boldsymbol{\alpha} + \alpha_t + \beta_1\, S_{bt} + \varepsilon_{lbt}, \tag{5}$$

using a linear probability panel specification.

4.3 Loan maturity

We also assess whether the maturity of loans is affected by the signing of climate commitments in the loan-level setting by estimating:

$$MtM_{lbt} = \boldsymbol{\alpha} + \alpha_t + \beta_1\, S_{bt} + \gamma_1\, EI_{lbt} + \gamma_2\, EI_{lbt}\, S_{bt} + \varepsilon_{lbt}, \tag{6}$$

where MtM_{lbt} is the maturity (in months) of loan l and EI_{lbt} was defined above. The coefficient of interest, γ_2, indicates the differential effect of signing climate commitments on average maturity of loans to firms in higher-emitting sectors. If green commitments lead banks to reduce the maturity of loans to high-emitting sectors, $\gamma_2 < 0$. We estimate this regression with varying set of fixed effects, $\boldsymbol{\alpha}$, in addition to year fixed-effects, α_t.

5 Empirical findings

The empirical approach described in Section 4 aims to address three main empirical questions. Did the signing of green commitments reduce the emission exposure of banks' portfolios? Did the signing of green commitments reduce the probability of issuing a loan to borrowers in high-emitting sectors? Did the signing of green commitments shorten maturities of loans to firms in higher-emitting sectors?

In broad strokes, we find that there is no robust association between banks' voluntary climate commitments and the composition or characteristics of their syndicated loan portfolios across industries. Specifically, while we do observe that all banks have reduced the share of loans to highly emitting industries, there is no difference between the banks that signed climate commitments and those that did not. This finding holds even when we focus our analysis on loans extended only to high-emitting sectors. Similarly, we do not find evidence of shortening maturities to borrowers in sectors with higher emissions. Given that we essentially find a null effect on loan composition in our benchmark analysis, we conduct extensive additional analysis to stress-test our findings. Our robustness analysis corroborates our main findings as described in Section 6.

One potential concern in our analysis is that the decision to sign a climate commitment is endogenous, that is, banks with greener portfolios are more likely to sign climate commitments. We test this hypothesis using a Cox proportional hazard model of the form:

$$h_b(t|EE_{bt}) = h_0(t) \cdot \exp(\beta \cdot EE_{bt}),$$

where $h_b(t|EE_{bt})$ is likelihood of bank b signing a commitment at time t conditional on their emissions exposure at time t, EE_{bt}, and not having signed a commitment previously. $h_0(t)$ is the unconditional probability of signing a commitment at time t. We estimate specifications with and without bank fixed effects and report results in Table A4. While we do not find a statistically significant effect in some specifications without bank fixed effects, we observe a statistically significant hazard ratios greater than one ($\exp(\hat{\beta}) > 1$) in the specification with bank fixed effects for PRI and TCFD, indicating that higher portfolio emissions exposure is associated with an elevated probability of signing a climate commitment. This suggests that commitment decision is not driven by banks with historically low exposure, but rather that banks are *more* likely to become signatories as their emissions exposure increases.

5.1 Bank-level local projections

The results from the estimation of LP-DiD equation (3) for PRI, TCFD, and PRB are reported in Figure 4, with the shaded areas indicating 95-percent confidence intervals. The panels report impulse response functions considering a horizon of up to 3 years before and after signing a commitment. The results are similar across the three climate commitments — in all cases, we find no statistically significant change in emissions' exposure of institutions that became signatories of climate commitments relative to those that did not. Moreover, pre-treatment coefficient estimates are also not statistically different from zero, suggesting no evidence of pre-trends in our sample. Leaving statistical significance aside, the coefficient estimates are of the opposite sign relative to our hypotheses — with higher emission exposure following signing commitments.

The analysis shown in Figure 4 focuses on average emission exposure of bank portfolios. As discussed in Section 4, given that most emissions are concentrated in a handful of industries, we also analyze the share of loans extended to firms in the top 10 percent of emission intensity distribution by replacing the dependent variable in equation (3) with the share of loans extended to high-emission borrowers (which are listed in the Appendix Table A3). Results are reported in Figure 5. Similar to our previous findings, we find no statistically significant change in banks' emission exposure after becoming signatories of PRI, TCFD or PRB, nor any significant pretrends.

Finally, we evaluate the hypothesis that banks may have shortened the maturities of loans to borrowers in high-emitting sectors to comply with their green commitments. Figure 6 shows no statistically significant change in maturities once banks become signatories. We also do not find evidence of pretrends in the sample for PRB signatories. For the PRI regressions, however, we do find a visible upward pretrend, indicating that prior to signing PRI banks were lengthening maturities of their loans to high-emitting sectors. This trend disappears following the signing of PRI, which could potentially point to a causal effect. For TCFD signatories, we observe a downward trend pre- and post-signing, but those are not statistically significant.

In our robustness tests, which we discuss in Section 6, we have experimented with various definitions of emission exposure of bank portfolios as well as different statistical specifications. Overall, our conclusions are unchanged.

5.2 Loan-level estimates

We next turn to loan-level regressions. We estimate the effect of signing green commitments on the emission index of the borrowers as well as the probability of lending to borrowers in high-emission industries, defined as those in the top-10 percent of the emission intensity distribution. We also estimate the effect on maturity of loans extended to borrowers in higher-emitting sectors. Even though these regressions are static, the value of "Signatory" indicator remains 1 in all years following the signing of commitment. Therefore, this analysis will capture a delayed response to this change as well as an immediate response.

Emission Index We report our main results separately for PRI, TCFD, and PRB in Table 1. For each of the three climate commitments, we estimate equation (4) at the loan level with different sets of fixed effects. For PRI, since our sample includes banks that have signed commitments before the first year of our sample, we also include estimates for the subsample of new signatories only, which we label, "New PRI." For the local projection estimates, we only use the New PRI sample, as we cannot build separate samples (pre-and-post signature dates) of institutions that signed PRI prior to the start of our sample. We also assess the average behavior of the emissions index over time by estimating equations (3) and (4) with year fixed effects alone. The estimated coefficients are reported in the Appendix Figure A3. They show an overall decline in the emissions index relative to 2015, with the exception of a transitory increase in 2020, which we associate with the COVID-19 episode and explore in our robustness analysis of Section 6. These downward trends restate our observation of the overall decline in emission exposures shown in Figure 2.

Column (1) of each section of the table provides estimates at the loan level without bank fixed effects, which means that coefficients are identified by variation across banks as well as over time. Column (2) includes bank fixed effects, which means that coefficients are identified by within-bank variation over time but not across banks. Column (3) reports the results where we also add borrower country fixed effects to absorb any differences in regional specialization across banks. All regressions include year fixed effects to absorb any common year-to-year variation.

When we do not include bank fixed effects, we find that banks that signed PRI (in full sample or among New PRI) tend to lend less to highly-emitting sectors than non-signatories ($\beta_1 < 0$ in equation (4)). However, the coefficients switch signs and lose statistical significance when we include bank fixed effects. This means that the negative effect is driven by the time-invariant difference between banks that signed PRI at some point and banks that never did. Including country fixed effects does not alter these results. For banks that signed TCFD, the negative effect survives the inclusion of bank fixed effects, but the coefficients are never statistically significant. We find a positive but statistically insignificant effect of signing PRB on the emission index of borrowers.

Thus, these regressions confirm our bank-level finding that, at least after the 2015 Paris Accord, while there was an overall trend towards lending less to borrowers in high-emitting sectors, there was no differential reduction in lending to those sectors by banks that signed a green commitment.

Lending to borrowers in high-emitter industries As detailed in Section 4, another way to detect divestment from high-emission industries is to test directly whether the probability of lending to firms in these industries is affected by banks' signing of climate commitments. We do so by focusing on lending to high-emission industries, which we defined as those in the top decile of the country-industry emission intensity distribution. We choose the top decile because of the highly skewed nature of the distribution. To test whether this affects the results, we also estimate quantile regression version of our baseline specification at the 25^{th}, 50^{th}, 75^{th}, 90^{th}, and 99^{th} percentiles. We discuss these findings in Section 6. Results from estimating equation (5) using a linear probability model are reported in Table 2, with the same combinations of fixed effects as in the emission intensity analysis. We continue to find no significant effect of signing commitments.

In sum, these loan-level regressions suggest that there is no clear robust effect on the change in the allocation of loans to high-emitting industries as a result of banks making green commitments.

Effects on maturity Our results so far show little support for the hypothesis that the signing of climate commitments led banks to reduce their participation in loans to highly-emitting sectors. We next assess whether financial institutions changed the maturity of the loans to these sectors.

Specifically, we test whether banks changed their loan maturity practices by estimating equation (6) at the loan level. Results are reported in Table 3. Note that the focus now is not on "Signatory" indicator, but on the interaction between the emissions index and signatory indicator. A negative interaction coefficient would indicate that banks that signed green commitments lowered maturities of their loans to firms in higher-emitting sectors relative to firms in lower-emitting sectors. Note that we add a specification with year-bank, year-country, and country-bank fixed effects, which we can estimate because our focus on the interaction between bank-time-varying signatory indicator and country-industry-varying emission index. The Signatory indicator does not drop out of this specification because when we construct this indicator at loan level, we use month of commitment, so that there is a variance within a given year. Table 3 only shows evidence of a reduction in the maturity of loans extended by PRI signatories. This finding holds irrespective of the set of fixed effects included in the regressions. It disappears, however, when we consider the New PRI, TCFD or PRB samples.

Thus, in addition to a null effect of climate commitments on loan composition, we find no robust effect on loan characteristics in the years following the signing of the commitments.

6 Robustness tests

Given that we do not find evidence of the effects of signing climate commitments on bank lending patterns, we need to establish that this null result is not an artifact of our specific measure or our specific empirical approach. In what follows, we show that, overall, regardless of methodology or measures used, we are unable to find robust evidence of banks changing their lending practices to highly emitting sectors as a result of signing green commitments.

All tables and figures with robustness tests results are reported in the Online Appendix.

6.1 Alternative definitions of emissions exposure and climate commitments

In our benchmark analysis, we constructed an index of emission intensity shown in the Appendix Figure A1. We now test whether this monotonic transformation of emission intensity has an effect on our findings. We repeat our bank-level LP-DiD analysis as well as loan-level regressions with the measure of emission exposure or emission index replaced with the log of the weighted average emission intensity. The results show an unchanged pattern. The local projections show no statistically significant change in bank lending after subscribing to climate commitments. Loan-level regressions confirm these findings and show that the "greening" effect from subscribing to PRI and New PRI disappears once we include bank fixed effects. Other commitments show no effects, as in our benchmark results.

In creating emissions exposure of each bank, we used the full facility amount, regardless of the number of participants. Therefore, our results should be interpreted as decisions to participate in a loan of a given amount, regardless of the contribution. While we would like to include actual participant shares as weights, these are only reported for about 13% of the loans in our data. To see if any bias is generated by our decision to not weigh facility amounts, we repeat our benchmark local projections analysis using the facility amount divided by the number of participants in each loan. Our conclusions are unchanged.

We also considered three alternative measures of commitment in addition to PRI, TCFD, and PRB signing. Namely, the Environmental Pillar of the ESG index (E-score); the signing of the Equator Principles; and Net Zero commitments. The Equator Principles (EPs) are intended to serve as a common baseline and risk management framework for financial institutions to identify, assess and manage environmental and social risks when financing projects. The Equator Principles apply globally, to all industry sectors and to six financial products: project finance advisory services, project finance, project-related corporate loans, bridge loans, project-related refinance, and project-related acquisition finance. Equator Principles Financial Institutions implement the 10 Equator Principles through their internal environmental and social risk management policies, procedures and standards. Net Zero commitments are defined as the date a bank released a statement committing to achieving net zero emissions in their lending portfolio. We found no significant effects on the loan composition of either of these alternative measures once we control for bank fixed effects in the loan-level regressions.

6.2 Additional empirical specifications

In addition to including PRI, PRB, and TCFD commitments individually, we also estimated regressions with these three indicators included together: essentially, a signatory indicator takes on a value of 1 when either of the three commitments is signed. At the bank level, we repeat the local projections analysis with the signing event S_{bt} being the earliest date of signing any of the three commitments. At the loan level, we repeat our regression analysis, but allowing, alternatively, for the indicator being the earliest commitment signed, or the signatory indicator to increase by 1 every time an additional commitment is signed. We find that there is no significant effect of signing the first commitment either at bank or loan level, nor when we accumulate commitments. We also repeated this analysis for the effects on maturity. We found that signing the first commitment, or cumulative number of signed commitments do not affect maturity of loans to higher-emitting borrowers.

We also considered that climate commitments might not be reflective of the actual greenness initiatives (or actions) of banks. To account for this possibility, we include the Environmental Pillar of the ESG Index as a control variable, which we obtained for each bank in each year from LSEG Loan Connector. ESG Scores measure companies' ESG performance based on reported data in the public domain. The Score considers three pillars and 10 different ESG topics. The environmental pillar pertains to firms' resource use, emissions and innovation. The pillar weights are normalized to percentages ranging between 0 and 100. Our main conclusions hold and no climate commitment effect is observed once we include bank fixed effects.

In our benchmark bank- and loan-level regressions, we included year fixed effects. We report these estimated fixed effects in Figure A3. The left panel shows estimates at the bank-level while the right panel shows estimates at the loan level. Overall, estimates point to a decline in emissions exposure relative to the sample start. We confirmed this trend by also estimating our regressions with a linear trend, which yielded a negative coefficient. We find, however, that the effect of signing commitments is not affected by this modification. Moreover, we reestimated our local projections at the bank level using standard local projections (instead of difference-in-differences) and reached the same conclusions. We also entertained alternative constraints for the set of controls in our LP-DiD estimates, which helps us ascertain the presence of bias due to our short sample

(Herbst and Johannsen, 2024), by assuming the control set only includes banks that never signed an agreement or keeping the same set of banks as controls for all horizons. Our findings are, once again, unchanged.

Our benchmark specification does not control for demand effects. Even with country and year fixed-effects, there might be trends in demand for loan financing that may mask the effects of signing commitments. Since we do not have relevant data for individual borrowers and our data structure (list of loans) does not allow us to control for borrower or borrower-time fixed effects, we include, as proxy for demand trends, total lending from all banks to a given country in a given year or to a given country-industry cell in a given year in our emission-index regressions. We find that our main effects are essentially unchanged. The effect of total lending to a given country has no effect on the emission index of loans, while the effect of total lending to a given country-industry enters negatively. However, the effects of becoming a signatory continue to be statistically insignificant in all specifications that include bank fixed effects.

We also considered a less parametric regression. While our analysis of the emissions index reflects average emissions exposure of bank portfolios, and our analysis of lending to highest emitters focuses on the right tail of emissions distribution, we evaluate whether the effect is present in other distribution shifts. To this end, we estimate loan-level quantile regressions, with 25^{th}, 50^{th}, 75^{th}, 90^{th} and 99^{th} quantiles of emission intensity. If banks tilt their portfolios to greener assets, we would expect a positive effect of signing commitments on the low percentiles (25^{th} and 50^{th}) and negative effect on high percentiles (75^{th}, 90^{th}, and 99^{th}). Our findings still point to no significant effect of signing PRI, New PRI, or PRB on the composition of bank loans — there is no statistical difference between the coefficients on the signatory indicator across different quantiles. Interestingly, we do find a negative and statistically significant coefficient, at 10%, for TCFD at the 75^{th} quantile, but this result is reversed when we consider the 90^{th} and 99^{th} percentiles. Moreover, coefficients are statistically significant at the 25^{th}, 50^{th} percentiles, but they are negative (instead of positive). This suggests that banks that sign TCFD may reduce their exposure to emissions of borrowers in relatively clean industries, which contribute very little to overall emissions. This finding is consistent with a similar result in a recent contribution by Gu et al. (2026) at the firm level.

We also consider alternative levels of aggregation, clustering of standard errors, and combinations of fixed effects, as well as various lag structures, and our conclusions are unchanged.

6.3 Alternative samples

Our analysis is based on the data set constructed from all banks participating in each syndicate. Since our question is whether banks change their credit allocation decisions in response to their climate-related commitments, it seems natural to include all syndicate participants in our analysis. However, one may argue that originating a syndicated loan is a bigger decision (and commitment) than participating in one. Thus, we repeat our analysis for the data set constructed based on lead arrangers only. Results at loan level are similar to those reported in Section 5.

We also consider estimates for a subsample of banks that specialize in dirty industries. To do so, for each bank-year, we calculate the average share of loans extended to the utilities, oil and gas, and shipping industries, which correspond to the highest emission industries in the SIC listing. These shares are constructed as in Sharma (2025), where a bank loan share to a particular industry j at time t is defined as the share of credit extended relative to the overall share of credit to that industry by all banks in the sample. We define a bank as specialized in dirty industries if its share of loans extended to those industries is above the average share of loans extended to that industry by all banks in our sample. For this subsample of banks, we reestimate equations (3) and (4). Overall, our findings do not point to any robust change to lending practices among signatory banks specialized in dirty industries. The local projections show some decline in the emissions exposure of banks that signed TCFD in the year the commitment is signed, but this effect is temporary and is quickly reversed. The loan level estimates do not show any significant reduction in exposure once bank fixed effects are included.

Finally, given potential changes in lending practices due to the COVID-19 pandemic, we also considered limiting the sample to loans that originated before 2020. We estimate our main specification at the loan-level for each commitment only using loans from 2015 to 2019. Once again, we are not able to find significant changes to emissions exposures among PRI, New PRI, and PRB signatories. We do find, however, a statistically significant decline, at 10% significance level, in exposure among TCFD signatories. To further explore this finding, we estimate bank-level local projections as in equation (3) for the pre-COVID-19 sample. This sample constraint, however, significantly shortens the horizons of interest, as TCFD have no signatory banks prior to 2017. In unreported results (and available upon request) we consider a horizon of 2 years and do not find a statistically significant change to emissions exposure among TCFD signatories.

7 Conclusion

We present a number of empirical tests that evaluate the effect of banks signing green commitments on the industrial composition of their syndicated lending and the maturity of their loans across sectors. We found no significant changes in the lending practices of banks that signed green commitments. In the few instances where we found a statistically significant effect of becoming a signatory, the effect was either temporary or did not survive our robustness testing.

Overall, we conclude that banks that signed green commitments did not tilt their portfolio of loans any differently from those that did not, at least in the context of the syndicated loan market. Our results are based on industry-level data, and it is, therefore, possible that banks changed their portfolios by relocating funds toward more climate-friendly firms *within* industries. Unfortunately, our data are not granular enough to estimate these effects. An additional question we do not tackle in our analysis is whether changes to banks' behavior could lead (or have led) to increasing costs of green transition, particularly for industries that would need it the most. A growing literature touches on these issues (*e.g.*, Hartzmark and Shue, 2022, Chen, 2025, and Green and Vallee, 2025). Finally, we also do not address the question of whether the firms to which banks lend have become greener in any way. Since we rely on the measure of emissions that does not vary over time or across firms within a given country-sector, these are interesting questions that are left outside the scope of our analysis.

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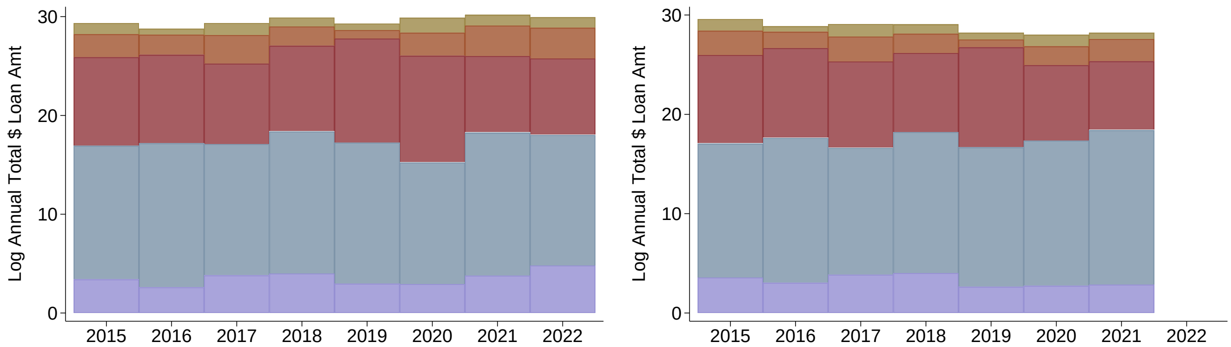
Figure 1: Industrial Composition of Loans by Commitment Status of Banks

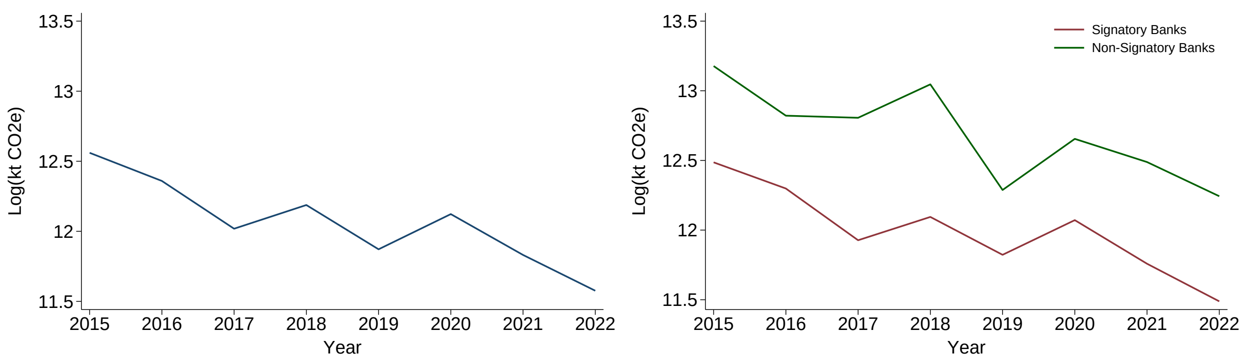


(a) Signatories of any commitment

(b) Nonsignatories

Panel (a) reports the total facility amount lent in each year to different industries by banks that sign either the PRI, TCFD, or PRB at any point in our sample. Panel (b) reports the total facility amount lent in each year to different industries by banks that sign no commitments in our sample.

Figure 2: Average Bank Emissions Exposure



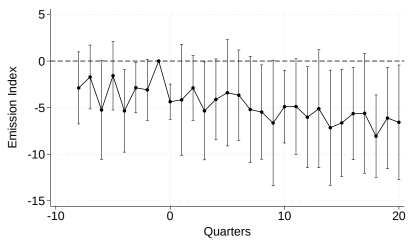
(a) All Banks

(b) By Signatory Status

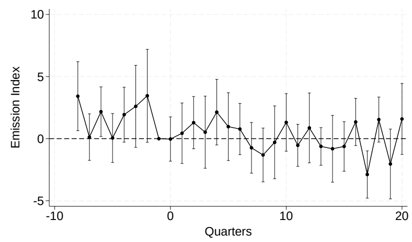
Panel (a) reports the average log facility-amount-weighted total emissions by an industry receiving a loan in our sample. Panel (b) reports the same statistic, comparing banks that sign either the PRI, TCFD, or PRB at any point in our sample and banks that never sign any of our three commitments.

Figure 3: Event Study Results

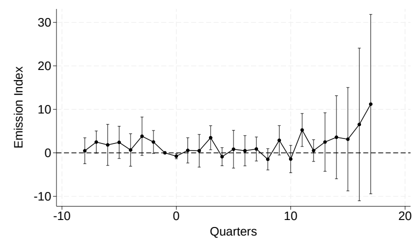
Emission Index



(a) PRI

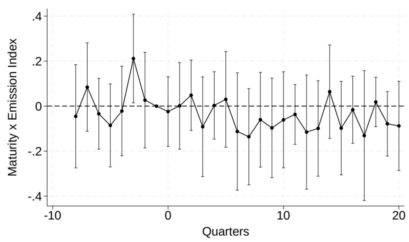


(b) TCFD

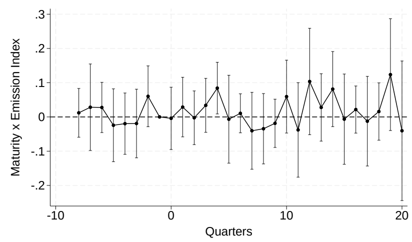


(c) PRB

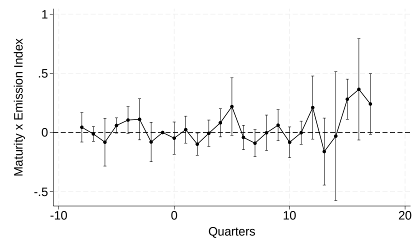
Maturity



(d) PRI



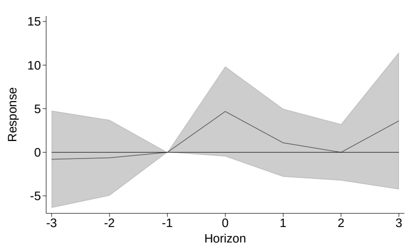
(e) TCFD



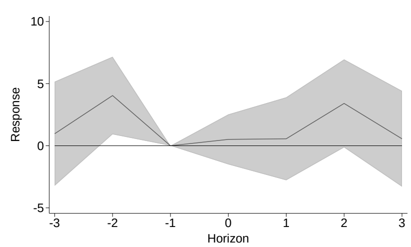
(f) PRB

This figure shows the coefficients β and 95% confidence intervals from loan-level regression of Emission Index on time relative to signing one of the agreements (equation (1)) in the top panel and coefficients γ from the regression of Maturity of the loans on time relative to signing one of the agreements interacted with Emission Index (equation (2)) in the bottom panel.

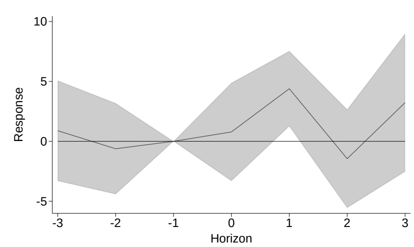
Figure 4: Local Projections Difference-in-Differences: Effect of Signing Commitments on Emission Exposure



(a) PRI



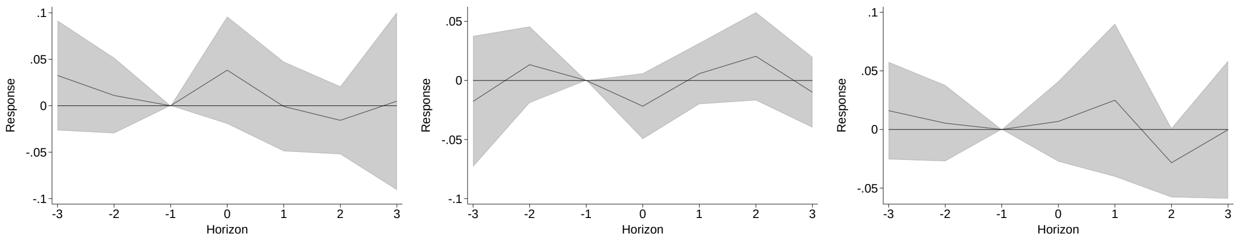
(b) TCFD



(c) PRB

Note: Dependent variable is a emission exposure of bank loan portfolio, computed as a weighted average of the emission index of all loans originated by syndicates with participation of bank b in year t using loan amounts (converted to USD) as weights. See equation (3) for the exact specification. Standard errors are clustered at the bank level and are robust to heteroskedasticity and serial correlation. 95% confidence bands.

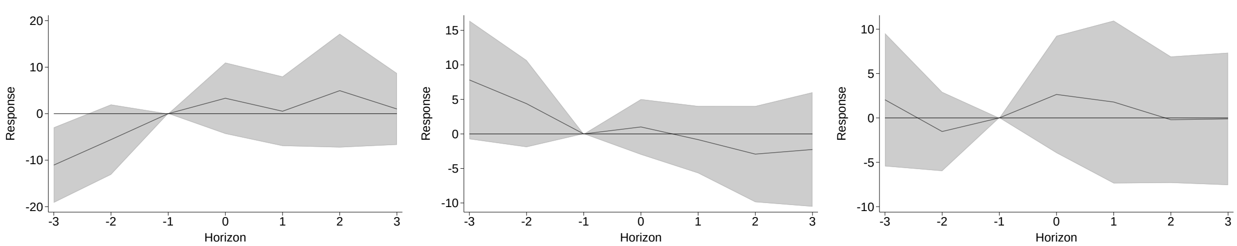
Figure 5: Bank Level LP-DiDs, Share of lending to highest emitters



(a) PRI (b) TCFD (c) PRB

Note: Dependent variable is a share of bank loans in the top decile of emission index. See equation (3) for the exact specification. Standard errors are clustered at the bank level and are robust to heteroskedasticity and serial correlation. 95% confidence bands.

Figure 6: Bank Level LP-DiDs, Maturity



(a) PRI (b) TCFD (c) PRB

Note: Dependent variable is the difference in the average maturity of loans given to top 10% emitters and loans given to median emitters. See equation (3) for the exact specification. Standard errors are clustered at the bank level and are robust to heteroskedasticity and serial correlation. 95% confidence bands.

Table 1: Effects of signing commitments on borrowers' emission index

Emissions Index	(1)	(2)	(3)	(1)	(2)	(3)
		All PRI			**New PRI**	
Signatory	-1.738***	0.491	0.532	-2.154*	0.142	0.159
	(0.414)	(1.061)	(0.998)	(0.836)	(1.187)	(1.198)
N	269,412	269,412	269,412	161,655	161,655	161,655
R^2	0.003	0.020	0.045	0.003	0.022	0.048
		TCFD			**PRB**	
Signatory	-0.254	-1.268	-1.212	1.542	0.247	0.190
	(0.815)	(0.746)	(0.709)	(0.868)	(0.891)	(0.763)
N	269,412	269,412	269,412	269,412	269,412	269,412
R^2	0.002	0.020	0.045	0.002	0.020	0.045
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	No	Yes	No	No	Yes

Note: Dependent variable is the emission index associated with the loan. See equation (4) for the exact specification. Fixed effects as indicated. Standard errors clustered at the bank and industry level. * indicates significance at 5% level, ** at 1% level, and *** at 0.1% level.

Table 2: Effects of signing commitments on the probability of lending to a high emitter

I(loan to top 10% emitter)	(1)	(2)	(3)	(1)	(2)	(3)
		All PRI			**New PRI**	
Signatory	0.002	0.010	0.010	-0.002	0.005	0.004
	(0.003)	(0.008)	(0.007)	(0.003)	(0.009)	(0.007)
N	269,412	269,412	269,412	161,655	161,655	161,655
R^2	0.002	0.016	0.079	0.002	0.020	0.083
		TCFD			**PRB**	
Signatory	-0.010	-0.013	-0.010	-0.004	-0.009	-0.009
	(0.009)	(0.008)	(0.007)	(0.005)	(0.007)	(0.007)
N	269,412	269,412	269,412	269,412	269,412	269,412
R^2	0.002	0.017	0.079	0.002	0.016	0.079
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	No	Yes	No	No	Yes

Note: Dependent variable is an indicator of borrower being in the top decile of our emission index, estimated using linear probability model. See equation (5) for the exact specification. Fixed effects as indicated. Standard errors clustered at the bank and industry level. * indicates significance at 5% level, ** at 1% level, and *** at 0.1% level.

Table 3: Main Results: Months to Maturity

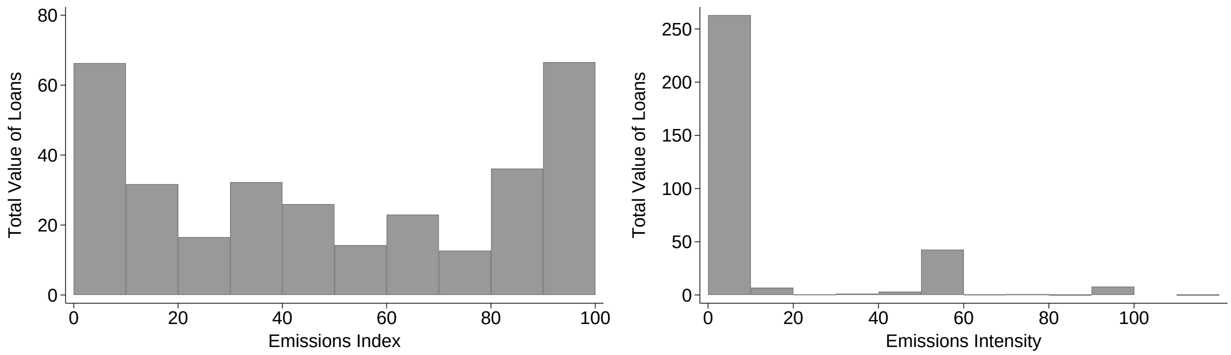
Months to Maturity	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	PRI				**New PRI**			
Signatory	4.480***	2.526	2.627	7.224*	5.084***	1.664	1.880	6.413
	(0.973)	(1.325)	(1.409)	(3.437)	(1.106)	(1.956)	(2.010)	(3.230)
Emissions index	0.101	0.096	0.105	0.098	0.100	0.096	0.106	0.098
	(0.074)	(0.081)	(0.073)	(0.057)	(0.074)	(0.076)	(0.072)	(0.056)
Emissions x sig.	-0.037	-0.042*	-0.039	-0.041***	-0.014	-0.019	-0.017	-0.025
	(0.063)	(0.020)	(0.023)	(0.006)	(0.044)	(0.051)	(0.046)	(0.026)
N	262,252	262,252	262,252	262,174	157,622	157,622	157,622	157,566
R^2	0.013	0.046	0.089	0.151	0.015	0.056	0.103	0.176
	TCFD				**PRB**			
Signatory	-0.885	-0.282	-0.245	0.402	3.386	-1.153	-1.073	-1.361
	(1.681)	(1.049)	(0.979)	(1.038)	(2.370)	(2.551)	(2.138)	(2.364)
Emissions index	0.065	0.060	0.071	0.063	0.068	0.063	0.073	0.068
	(0.061)	(0.065)	(0.060)	(0.048)	(0.061)	(0.064)	(0.060)	(0.048)
Emissions x sig.	0.037	0.036	0.032	0.033*	0.056	0.057	0.056	0.044
	(0.032)	(0.032)	(0.029)	(0.016)	(0.056)	(0.063)	(0.051)	(0.036)
N	262,252	262,252	262,252	262,174	262,252	262,252	262,252	262,174
R^2	0.011	0.046	0.089	0.150	0.014	0.046	0.090	0.150

Note: Dependent variable is maturity of the loan at origination, in months. See equation (6) for the exact specification. Fixed effects as indicated. Interacted fixed effects include year-bank, year-country, and country-bank fixed effects. Standard errors clustered at the bank and industry level. * indicates significance at 5% level, ** at 1% level, and *** at 0.1% level.

Appendix

Figure A1: Total Loans by Emissions

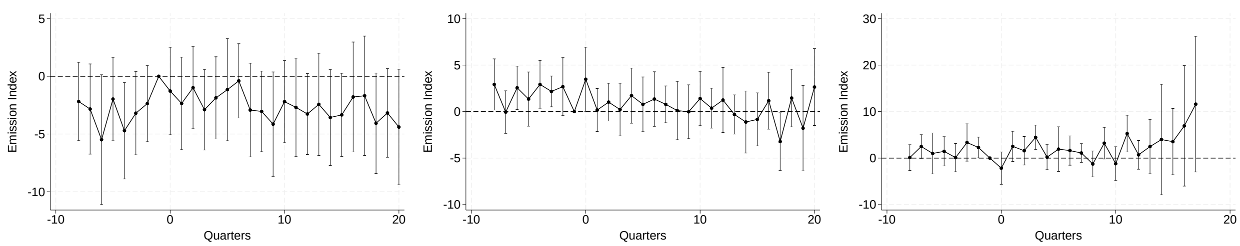
(a) Emissions Index (b) Emissions Intensity



Panel (a) reports the distributions of loan values by deciles of our emission index. Panel (b) reports the distribution of the log of total emissions over output.

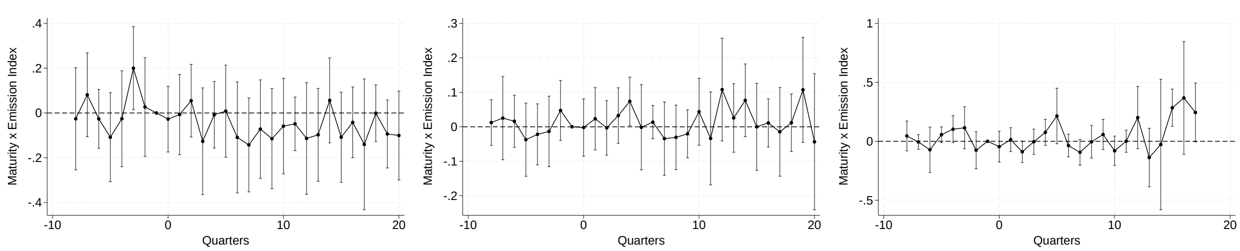
Figure A2: Event Study Results, Bank Fixed Effects

Emission Index



(a) PRI (b) TCFD (c) PRB

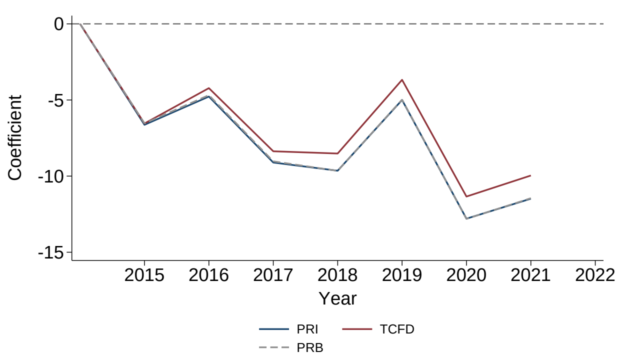
Maturity



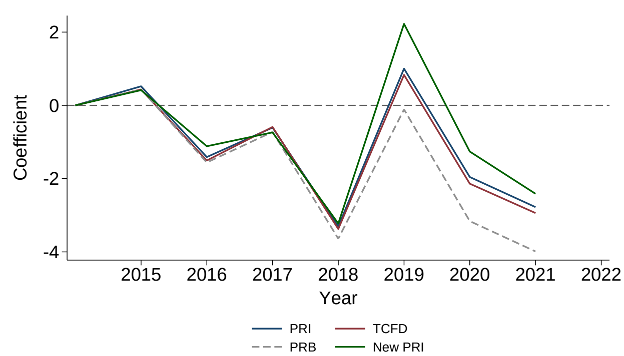
(d) PRI (e) TCFD (f) PRB

This figure shows the coefficients β and 95% confidence intervals from loan-level regression of Emission Index on time relative to signing one of the agreements (equation 1) in the top panel and coefficients γ from the regression of Maturity of the loans on time relative to signing one of the agreements interacted with Emission Index (equation 2) in the bottom panel.

Figure A3: Time Series of Year Fixed Effects Coefficients



(a) Bank Level



(b) Loan Level

Note: Plot of coefficients on each year fixed effect of our main regression specification, dropping 2015. See equation (4) for the exact specification.

Table A1: Green commitment dates

Bank Name	PRI Signing Date (1)	TCFD Signing Date (2)	PRB Signing Date (3)
ABN AMRO	2012m3	2017m11	2019m9
ANZ			2019m9
BBVA	2021m8	2017m12	2019m9
BMO Capital Markets	2019m12	2017m12	2021m1
BNP Paribas	2012m9	2017m6	2022m12
BOfA	2014m11	2017m6	
Bank of China	2019m12	2021m2	2021m7
Barclays	2016m4	2017m6	2019m9
BayernLB		2020m11	2021m8
CIBC World Markets		2018m3	
CM-CIC			2019m11
CaixaBank	2016m5	2017m12	2019m9
China Construction		2021m5	
Citi		2017m6	2019m9
Citizens Financial			
Commerzbank Group	2020m9	2020m9	2019m9
Commonwealth Bank		2018m3	2019m10
Credit Agricole	2010m3	2017m12	2019m9
Credit Suisse	2014m1	2017m11	2019m9
DNB Markets	2006m10	2017m6	2019m9
Danske Bank	2010m2	2018m9	2019m9
Deutsche Bank	2012m5	2018m9	2019m9
Fifth Third Securities		2020m9	
First Abu Dhabi		2019m12	2021m10
Goldman Sachs	2011m12	2018m9	2021m3
HSBC	2006m6	2017m6	
ICBC			
ING		2017m6	2019m9
Intesa Sanpaolo		2018m10	2019m9
Jefferies LLC			
KeyBanc Capital			
LBBW	2009m10		2018m9
Lloyds Banking		2017m12	2019m9
MUFG	2006m4		2019m9
Macquarie	2015m8	2019m4	
Mediobanca	2019m9	2022m3	2021m5
Mizuho	2006m9		2019m9
Morgan Stanley	2006m4	2017m6	2019m9
National Australia Bank	2019m2	2017m10	2019m9
Natixis	2019m8	2021m2	2019m9
Nomura	2011m3		2020m5
Nordea	2007m1	2018m12	2019m9
OCBC		2019m11	
PNC Bank			
RBC Capital	2015m8	2020m6	
Rabobank	2022m7	2017m10	2022m12
SEB		2018m5	
SG Corporate		2021m9	
ScotiaBank		2018m2	
Standard Chartered Bank		2017m6	2019m9
Sumitomo Mitsui	2019m1	2017m12	2019m9
TD Securities			
Truist Financial			
UBS	2009m4	2017m6	2019m9
UOB		2019m11	
US Bancorp			
UniCredit		2020m1	2019m10
Wells Fargo		2019m11	
Westpac		2017m12	2019m9

Table A2: Loan Characteristics

Bank Name	Observations	Facility Amount		Months to Maturity		Total Emissions	
		Mean	SD	Mean	SD	Mean	SD
Signatory Banks							
ABN AMRO	1,600	52.90	64.95	59.68	43.63	2,490.12	8,427.48
ANZ	1,246	56.70	95.69	42.96	22.52	628.98	1,108.14
BBVA	5,003	56.03	179.88	63.29	41.73	1,382.06	5,945.73
BMO Capital Markets	7,619	42.44	96.03	53.73	20.41	1,967.57	6,540.28
BNP Paribas	11,784	63.79	197.66	61.71	35.46	2,205.36	8,114.65
BOfA	16,016	75.44	185.57	50.42	22.40	2,283.65	7,675.11
Bank of China	3,492	71.53	130.75	54.24	45.96	3,165.51	9,706.36
Barclays	9,447	74.24	186.80	56.45	26.40	2,002.90	7,184.17
BayernLB	1,522	46.60	85.70	77.30	65.41	2,006.95	7,641.50
CIBC World Markets	3,431	36.00	60.42	47.63	30.27	4,581.33	11,529.37
CM-CIC	2,781	31.09	51.38	72.04	44.42	656.55	3,764.08
CaixaBank	2,719	48.30	134.02	77.27	60.15	1,014.64	5,385.68
Citi	14,393	76.92	280.14	51.40	22.45	2,610.86	8,317.48
Commerzbank Group	3,511	56.23	98.72	51.44	32.84	970.56	5,163.94
Commonwealth Bank	1,218	39.86	75.97	51.60	33.50	3,688.23	10,477.92
Credit Agricole	8,408	48.33	95.76	68.25	42.32	2,556.81	8,932.08
Credit Suisse	7,542	69.01	168.48	58.45	23.41	2,351.24	7,839.84
DNB Markets	1,452	60.36	94.60	58.14	34.70	2,204.83	8,343.35
Danske Bank	1,062	75.95	136.65	57.57	37.56	142.23	365.45
Deutsche Bank	9,147	68.16	183.51	56.93	28.34	1,522.32	5,979.20
Fifth Third Securities	5,107	42.15	164.00	53.40	17.53	2,142.64	7,119.05
First Abu Dhabi	296	60.26	88.07	30.18	27.28	961.77	5,237.19
Goldman Sachs	8,630	88.09	327.58	57.52	23.89	2,076.54	7,265.89
HSBC	9,084	65.40	168.80	52.88	23.73	1,485.12	6,308.95
ING	7,830	53.01	94.90	60.02	35.57	2,366.38	8,253.68
Intesa Sanpaolo	2,909	54.79	94.05	60.48	35.88	1,067.53	5,370.87
LBBW	1,995	53.72	80.00	76.02	55.63	632.67	3,650.52
Lloyds Banking	1,686	82.78	190.15	60.00	52.65	592.70	3,362.05
MUFG	10,836	59.36	147.24	58.09	50.29	4,316.49	11,326.77
Macquarie	1,751	53.78	142.80	62.86	26.51	1,213.32	4,154.02
Mediobanca	690	72.39	96.19	53.80	20.30	293.80	2,134.02
Mizuho	8,291	65.02	170.27	58.11	55.65	3,376.02	10,080.94
Morgan Stanley	5,837	82.85	198.79	56.44	22.73	2,742.36	8,685.60
National Australia Bank	1,474	40.62	52.68	55.44	37.09	3,735.86	10,610.47
Natixis	3,769	56.16	96.54	65.73	47.08	2,775.30	9,106.92
Nomura	1,615	57.47	154.47	62.70	22.60	2,233.08	7,934.89
Nordea	1,492	71.34	121.81	50.10	23.16	115.06	273.45
OCBC	340	54.83	104.65	61.79	57.63	1,778.16	6,477.75
RBC Capital	7,066	65.29	182.90	55.08	21.86	3,337.83	9,689.06
Rabobank	3,206	44.03	58.00	59.74	47.89	4,036.22	11,098.34
SEB	1,696	65.67	123.81	62.09	40.76	384.12	1,761.71
SG Corporate	6,756	57.70	109.29	64.57	47.74	2,232.97	8,166.81
ScotiaBank	2,980	73.31	131.03	47.62	22.96	4,645.59	11,635.19
Standard Chartered Bank	1,796	82.35	136.90	43.49	43.24	1,491.99	5,992.72
Sumitomo Mitsui	10,305	54.44	158.28	63.36	58.69	2,794.88	9,013.68
UBS	2,966	63.90	147.75	59.66	23.72	1,464.15	5,866.21
UOB	392	52.33	77.31	39.63	28.54	383.13	879.06
UniCredit	5,243	57.08	108.38	62.93	40.62	394.88	1,887.64
Wells Fargo	10,525	74.57	170.45	48.09	20.34	3,205.80	9,357.95
Westpac	909	45.13	101.43	50.36	36.02	678.06	1,014.31
Non-Signatory Banks							
Jefferies LLC	3,795	51.90	90.76	66.07	19.47	1,441.13	5,205.84
KeyBanc Capital	4,926	40.89	81.67	52.19	20.47	5,593.33	12,676.83
PNC Bank	6,147	57.97	140.11	48.64	18.73	3,358.77	9,628.16
TD Securities	3	75.37	26.64	241.00	130.50	119.46	0.00
Truist Financial	7,244	52.19	99.50	53.61	19.01	3,076.64	9,205.28
US Bancorp	6,148	66.49	182.49	46.76	19.82	3,125.62	9,204.99

Note: Summary statistics on the loan characteristics for each bank in our sample, split between signatory banks (banks that sign either PRI, PRB, or TCFD at any point in our sample) and non-signatory banks (banks that do not sign any commitments in our sample). Facility amount is the total dollar value of the facility (in millions of dollars) divided by the number of contributors; maturity is in months; the emissions exposure of the loans is in thousands of carbon dioxide equivalent units.

Table A3: Highest Emitting Industries Across Countries

Industry (1)	**Average EI** (2)	**Industry** (3)	**Top Decile Prob.** (4)
Coke and Petroleum Manuf.	98.13	Coke and Petroleum Manuf.	0.99
Water Transport	92.62	Air Transport	0.97
Air Transport	91.64	Water Transport	0.90
Electricity & Gas Supply	91.31	Chemicals Manuf.	0.85
Chemicals Manuf.	90.35	Land Transport	0.62

Note: Summary statistics on the highest emitting industries across countries. Column (1) shows the 5 highest emitting industries across countries when measured as the average percentile of an industry's emissions index across all countries in our sample, which we show in column (2). Column (3) shows the 5 highest emitting industries when measured as the probability that an industry places in the top decile of a country's emissions index across all countries in our sample, which we show in column (4).

Table A4: Effect of Emissions on Signing Probability

Signatory	(1)	(2)	(1)	(2)	(1)	(2)
	PRI		**TCFD**		**PRB**	
Emissions Index	1.00	1.04***	1.02***	1.03***	1.02**	1.02
	(0.006)	(0.013)	(0.006)	(0.012)	(0.007)	(0.014)
N	431	431	431	431	431	431
Bank FE	No	Yes	No	Yes	No	Yes

Note: Dependent variable is signing the commitment, independent variable emission exposure, measured as bank-year weighted average of emission index. Cox proportional hazard model, with hazard ratios reported. Note that Null hypothesis of no effect is $\beta = 1$. Fixed effects as indicated. * indicates significance at 5% level, ** at 1% level, and *** at 0.1% level.