Do Voluntary Initiatives Make Loans Greener? Evidence from Project Finance

Tobias Berg, Robin Döttling, Xander Hut, Wolf Wagner*

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Abstract

We analyze how lender initiatives affect the greenness of loan origination in the project finance market. This market is of key importance for financing large-scale, climate-relevant projects globally, and we can directly classify the environmental impact of the funded projects. We exploit a tightening in the Equator Principles (EP) that introduced comprehensive climate risk management requirements for loans to environmentally-sensitive projects. Using lender- and loan-level analyses, we find that EP members did not shift lending to greener projects relative to non-members. The result is robust to a wide set of modeling choices. Taken together, the evidence points towards limitations in relying on lender-driven initiatives in the transition towards a greener economy.

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*Berg (berg@finance.uni-frankfurt.de) and Hut (hut@finance.uni-frankfurt.de) are affiliated with Goethe University Frankfurt. Döttling (doettling@rsm.nl) and Wagner (wagner@rsm.nl) are with Rotterdam School of Management, Erasmus University. For helpful comments and suggestions, we thank Mathijs Cosemans, Mathijs van Dijk, Emilia Garcia-Appendini, Caterina Rho, Naciye Sekerci, Laura Trinchera, and the participants of presentations at Goethe University Frankfurt, the Neoma Business School Sustainable Finance Conference, the Benelux Corporate Finance Days, the Imperial College New Frontiers in Climate Finance Conference, the GRETA Credit Conference, the CEPR Paris Symposium, and the EUROFIDAI-ESSEC Paris December Finance Meeting. Berg and Hut acknowledge financial support from the European Research Council, project 101044011. A previous version of this paper was titled "Do Voluntary Pledges Make Loans Greener?"

1 Introduction

Many lenders join voluntary initiatives that commit their members to account for climate change in their lending activities. These initiatives range from commitments to implement climate-related financial disclosure, to practice climate risk management, or to support the transition to a net-zero economy. They have the potential to speed up the green transition in loan origination. However, adhering to the requirements laid out in a green initiative may be burdensome and costly, potentially giving lenders incentives to commit only to less demanding goals or not to act on their commitments. This raises the question of whether green initiatives are effective in incentivizing lenders to originate greener loans.

We examine this question in a setting that is of primary importance for the green transition: the global market for project finance (PF). Project finance accounts for a large share of new developments in renewable energy and fossil-fuel energy globally. In 2022, the PF market financed 953 large-scale projects globally worth $363.1 bn (Refinitiv, 2022). PF loans support more than half of the global renewable energy market (52% in 2015 according to FS-UNEP (2016)). Additionally, 60% of new coal capacity (the world's highest-emitting energy source) between 2010 and 2023 was financed through PF.[1]

Examining the PF market also has an important advantage as an empirical setting: The environmental impact of expenditures funded by PF loans is observable because PF loans support single-purpose developments such as wind farms and coal mines, for which project descriptions are available. We use the project descriptions to directly measure the environmental impact of each loan. In contrast, prior studies have often proxied the greenness of a corporate loan by the recipient firm's overall greenness, as it is typically not possible to

[1]This estimate assumes that Chinese coal developments have the same share of PF funding as those in the rest of the world. Global Carbon Budget (2023) documents that coal is responsible for 41% of global carbon dioxide emissions in 2022. We combine data from Global Energy Monitor (2023) and Global Energy Monitor (2024) on newly developed coal plants outside of China (for which the data is unavailable) for our 60% estimate.

observe whether a specific loan supports (incremental) green or brown expenditures. This distinction is particularly relevant for our purpose because significant "greening" activities take place in firms that may be classified as brown based on their ESG score or carbon emissions. For instance, firms with low ESG scores are important green patent innovators (Cohen et al., 2021), and PE investment in fossil fuels can cause a switch to greener technologies locally (Kumar, 2023).

The leading green-lender initiative in the project finance market is the Equator Principles (EP). The EP were established in 2003 and now have 131 financial institutions as members, including many of the world's largest banks. The EP are the main industry framework for determining, assessing, and managing environmental and social risks in project finance globally. Lenders view the EP as an important commitment, as witnessed by their communication with stakeholders. For example, EP members often devote large sections of their annual reports to a discussion of how they implement the EP. Table 1 further shows that 72% of the 25 largest banks in the global syndicated loan market (regardless of whether they are an EP member or active in PF) refer to the EP in their 2022 ESG reports. This compares to 68% for the Net Zero Banking Alliance (NZBA) and 88% for the Task Force on Climate-related Financial Disclosures (TCFD). Importantly, lenders also face external visibility and pressure on the EP, through NGOs and proxy firms but also because of transparency requirements laid out in the EP.

Our analysis exploits the revision of the EP to version 4 (EP4). This revision was implemented in October 2020 and tightened previously applicable standards. Its most important change is a new requirement to undertake a comprehensive climate risk assessment for new PF loans with high emissions or other environmental externalities. The funded projects and their risk classifications are published on the EP website and thus expose members to external scrutiny. From a member's perspective, EP4 amounts to significant new requirements for making environmentally-sensitive loans. This allows us to estimate the impact of

a tightening of the environmental requirements within a green initiative on its members in a difference-in-differences setting.

We use the project descriptions tied to new PF syndicated loans to classify the environmental impact of the loan. We provide two alternative approaches to classification. The first approach limits the sample to energy projects and classifies projects as either renewable or fossil-fuel energy based on keyword matching (examples: solar, wind, or biomass for renewables, and coal, crude, or oil for fossil-fuel energy). Using this approach, we can classify 57% of all the projects in the full sample. This classification is very precise; we manually confirm that the measurement error is small. The second approach uses OpenAI's GPT-4 model to classify projects into green, neutral, or brown. This allows us to better exploit the information contained in the unstructured textual project descriptions and classify all projects in the entire sample.

We first examine how EP4 affects the greenness of loan origination to projects at the lender-level. Specifically, we run a difference-in-differences (DiD) model around the implementation of EP4, with the outcome variable being a lender's shares of green or renewable energy lending in a given year. For either of the two classifications, we do not observe a significant shift to greener lending, or to any other lending category (neutral or brown) by EP members relative to non-members. The estimated coefficients are close to zero and fairly precisely estimated, indicating that insignificance is not the result of a lack of statistical power. This provides initial evidence that the implementation of EP4 does not affect the greenness of funded projects.

We continue by analyzing the robustness of the results to a wide range of modeling choices, including different definitions of treated and control lenders, different fixed-effect specifications, and different proxies for the greenness of lending. In total, we run 480 specifications for each of our main regressions. Irrespective of modeling choices, with one exception discussed in the following paragraph, we do not detect any consistently significant effect of EP4

on lending outcomes, with the estimated coefficients generally being small and statistically indistinguishable from zero.

The one exception is the group of small lenders, representing less than ten percent of project financing volume, where we do find a significant decline in brown lending post-EP4. This finding has three implications: First, onerous requirements can deter the smallest lenders, thereby affecting bank lending industry dynamics. Second, any study that puts a large weight on very small lenders might identify significant effects, even though the affected lenders contribute little to aggregate lending volumes. Third, within our setting, we can pick up EP4-induced changes in lending practices if they occur. This provides further confidence in the validity of the no-results in our main sample.

We complement the lender-level analysis with a more granular loan-level analysis. This allows us to control for demand effects, using pseudo-borrower controls similar to Degryse et al. (2019). Consistent with the lender-level analysis we do not find that loans originated by EP members become greener after the implementation of EP4. The loan-level analysis also permits examining whether the characteristics of a loan of a given greenness change. It may be that post-EP4, members originate larger green loans and green loans with longer maturities. However, using triple-difference analyses with loan size and maturity as dependent variables, we do not find evidence supporting this conjecture.

Even though EP4 has no effect in the overall sample, it may be effective in specific subsamples where its incremental effect is expected to be most pronounced. We consider two such subsamples. We restrict the lender-level analysis to lenders outside the EU because lenders face less stringent climate policy there, indicating that climate requirements in EP4 could have more effect. For the loan-level analysis, we consider the subset of loans to projects in so-called non-designated countries because the EP are generally stricter for those projects. Both analyses again yield insignificant results in the respective subsamples.

We argue that our null results are unlikely due to data or modeling reasons. First, our

focus on PF loans permits a clean measurement of the environmental impact because we observe the project that is funded through the loan. Second, our null results persist over a very large range of modeling choices and considering different groups of loans. Third, our main difference-in-differences estimates are well-powered, with point estimates close to zero. While the loan-level triple-difference estimates focused on loan size and maturity are less well-powered, the estimates change signs, with roughly as many positive as negative point estimates when we consider a range of different specifications. Fourth, we can detect EP4-induced changes to lending practices where they occur—within the subset of small lenders responsible for less than ten percent of the aggregate lending volumes. This makes it unlikely that there is a shift to greener lending that we are unable to detect due to limited statistical power.

This points to the ineffectiveness of the EP4 revision in promoting green lending as an explanation behind our null results. Green initiatives may be ineffective, for instance, because lenders commit only to less demanding goals, or do not follow through on commitments made. We are agnostic about which of these two explanations drives our null results because we cannot directly observe lenders' risk management practices. It is important to note that we cannot rule out that EP4 has important societal benefits by forcing financial institutions to better manage climate risks that are inevitably linked to environmentally-sensitive projects. However, thorough and comprehensive risk management is likely to be costly for lenders, and should therefore lead to lenders originating fewer loans for brown projects – inconsistent with our results.

Our findings have immediate relevance for policymakers implementing the transition to a greener economy. They caution against relying on voluntary industry initiatives to achieve the transition as these may not necessarily result in a shift towards greener projects.

1.1 Related Literature

Several papers have studied the effects of banks signing up to green initiatives. Broadly, the literature provides mixed evidence on the impact of green initiatives on green loan origination and borrower outcomes. Kacperczyk and Peydró (2021) document that banks reduce lending to firms with more carbon emissions after signing up to the Science Based Targets initiative, but find that this does not improve the environmental performance of the borrowers. Degryse et al. (2023) find that banks signing up to the United Nations' Environment Program Finance Initiative reward green firms with cheaper syndicated loans. Hasan et al. (2023) similarly find that lenders signing up to the Task Force on Climate-Related Financial Disclosures (TCFD) reduce lending to polluting firms and that this, in turn, improves the firms' environmental performance. By contrast, Sastry et al. (2024) find no effect on lending outcomes for European banks signing up to Net Zero Banking Alliance. Similarly, Böhm et al. (2025) find no evidence that banks with more shareholders who are signatories of the Principles of Responsible Investment (PRI) shift lending away from firms with higher carbon emissions. Amiram et al. (2021) specifically study the EP. They examine a small subset of EP members (four large U.S. banks that joined the EP between 2003 and 2006) and find that, after joining the EP, they reduced spreads in syndicated loans to firms, and borrowing firms subsequently improved environmental ratings.

We contribute to this literature on several levels. First, we examine the project finance market, an underexplored market that is of paramount importance for the green transition. Second, we can directly classify the environmental impact of the expenditures financed by a loan as opposed to using firm-level greenness as proxy for loan impact.[2] Third, we investigate the effect of a tightening of an initiative on existing members, rather than the effect of

[2]After our paper became publicly available, the paper by Sastry et al. (2024) added a sub-section that analyzes project finance, in line with our argument about the usefulness of project finance for this purpose. Their approach focuses on Eurozone banks and classifies projects as renewable energy based on project names.

becoming the member of an initiative. This is an important change of focus as many of the leading initiatives age and develop a stable member base, making the "intensive margin" (change of the requirements among an existing group of members) important to study next to the "extensive margin" (changes in membership).

Besides industry-wide initiatives, other studies have examined the effect of greening activities by individual banks. Green and Vallee (2024) study banks that introduce policies to stop financing coal. They document that these policies negatively affect the financing and operation of coal assets, resulting in a reduction in carbon emissions. Giannetti et al. (2023) study banks that emphasize sustainability in their annual and sustainability reports and document that these lend more to brown firms.

There are several other papers specifically studying the EP. Sautner et al. (2024) study the pricing implications of the EU taxonomy in the syndicated loan market. Their analysis relates to our paper because it uses EP membership as a proxy for green preferences to document that EP members offer lower interest rates for firms with better EU taxonomy alignment. Several other papers study the EP without focusing on the greenness of lending. Eisenbach et al. (2014) study the performance of EP members after they join, finding financial benefits for institutions that adopt the EP. Scholtens and Dam (2007) describe how EP members and non-members differ. They document that the earliest EP members are larger banks with more developed corporate social responsibility policies than other banks. Contreras et al. (2019) also study the characteristics of EP members, highlighting peer pressure and collaboration with current EP members as predictors of EP membership. We are the first to study the impact of the EP on the greenness of the loans that the principles apply to: those funding developments through project finance.

2 Institutional Setting: Equator Principles

The EP are a risk management framework focused on environmental and social (ES) risk in the PF market. Their main goal is to provide a framework for determining, assessing, and managing environmental and social risks in project finance. There is also a secondary motive to have a positive societal impact.[3] The EP framework applies globally to any new project that fits certain criteria. For example, it is applied to any PF loan with a capital cost of at least US$10 mln. Besides PF loans (the focus of our study), it also applies to PF advisory services (PFAS), project-related acquisition finance, and broader products in the PF market.

The EP framework was started in 2003 and has grown to include 131 lenders by November 2024. These lenders are large players in the PF market and are jointly involved in more than half of the PF syndicated loans in our sample. The EP framework initially focused only on PF loans. The first revision (EP2) in 2006 extended the scope to include also PFAS. EP3 (implemented in 2013) added requirements for emissions estimations and reporting. Our study focuses on the last revision of the EP, EP4. EP4 was introduced in October 2020 and tightens climate risk management practices as we explain further below (a more extensive summary of the development of the EP framework over the years is available on page 8 of Equator Principles Association (2023)).

The EP are seen as an important initiative by banks, at least as witnessed in their investor communications. Table 1 summarizes information from annual reports and Environmental, Social, and Governance (ESG) reports for the 25 largest banks in the global syndicated loan market. Specifically, it contains information on how frequently the EP and other green

[3]The Association (EPA) strategy states: "We have adopted the Equator Principles to have a positive impact on the projects we finance." and "We must continue to work collaboratively and dynamically to manage impacts to climate, people and biodiversity." See Equator Principles Association (2022), page 9 and https://equator-principles.com/about-us/.

initiatives are mentioned in these reports (details on data collection are contained in Appendix A.1). For example, in 2022 the EP are mentioned in 72% of the ESG reports with a total 395 total mentions. Among the EP banks (19 out of the 25 banks) all mention the EP (the exception being BNP Paribas, which instead provides a separate EP report on its website). All other initiatives (the Net Zero Banking Alliance (NZBA), the Carbon Disclosure Project (CDP), the Principles of Responsible Banking (PRB), and the Science-Based Target Initiative (SBTi)) are mentioned less frequently. The exception is the TCFD, which is more frequently mentioned (in 88% of ESG reports and a total of 601 mentions).

The prominence of the EP is noteworthy as they apply to only a subset of loans for banks (essentially, PF loans), whereas the other initiatives are significantly broader in scope. Banks also often discuss the EP in detail in their ESG reports, for example in a dedicated section. Table 1 also contains information from annual reports collected from 2019 to 2022 (compared to ESG reports, annual reports are fairly standardized over time and can hence be collected over a period of time). A similar picture emerges. The TCFD is mentioned most frequently, followed by the NZBA, and then the EP (in 2021–2022; the NZBA was initiated in 2021).

Besides banks viewing the EP as an important initiative themselves, they also face external pressure on the EP. For example, Wells Fargo and Citigroup have faced criticism from NGOs for violating EP principles. Some proxy firms have also indicated that they will vote for shareholder proposals to study or implement the EP.[4] EP criteria are also explicitly incorporated into several projects financed by EP banks.

The most important element in EP4 is a new requirement to apply climate risk assessments to newly originated projects with high emissions or other environmental externalities.[5]

[4]See for example here for Wells Fargo and Citigroup and here for proxy advisory firm Horizon funds and investment firm Reynders, McVeigh Capital Management.

[5]EP4 also broadens the scope of the EP to include refinancing and acquisition finance, and it increases requirements within "designated countries", defined as countries that are both OECD member and on the World Bank High Income list.

We confirmed with practitioners who are involved in implementing the EP at a major EP member, that these climate risk assessments are the most impactful change within EP4.[6] They also confirmed that the newly required climate risk assessments are a significant effort for banks and that they largely affect brown loans. Banks also explicitly refer to the EP4 revision in their reports. For example, in their 2020 annual report, Mizuho Bank writes that one of the main revisions of EP4 is "*Enhanced measures to address climate change (added Climate Change Risk Assessment)*" and in Barclay's 2020 ESG report we read: "*[T]he Equator Principles Association (EP Association) adopted a fourth iteration of the Equator Principles (EP4) which came into effect in October 2020. Barclays has aligned its policies and procedures to new commitments[.]*"

EP members have incentives to implement climate risk assessments, first because they face external scrutiny on EPs but also because their outcomes are partly disclosed. According to the EP4 guidelines, EP member clients are required to, at a minimum, have a summary of the Environmental and Social Impact Assessment (ESIA) available online and to report greenhouse gas emission levels annually for projects with large emissions. Overall, EP4 amounts to a demanding increase in climate risk management standards that predominantly applies to a subset of loans (brown loans). Therefore, we hypothesize that EP4 results in a shift from brown to green project finance among EP members.

Exploiting the implementation of EP4 has an important advantage for identification. It allows us to estimate the effect of a new climate-related requirement as the implementation of EP4 (in 2020) is plausibly exogenous to factors that led to individual institutions joining the initiative (which itself was established in 2003). Most lenders in fact joined the EP well before EP4 was implemented and hence are unlikely to have anticipated the specific new

[6]Consistent with this, the inclusion of refinancing and acquisition finance covers 1.7% of the EP deals in 2022 (Equator Principles Association, 2022). Similarly, increased requirements for designated countries only apply when host country laws are not strict on specific components of ES risk, which we have verified is not a common case.

EP4 requirements (and our results are robust to excluding the few lenders that join shortly before EP4).

Focusing on EP4 also has advantages as an empirical setting along other dimensions. First, as the EP initiative has many members a single lender's individual preferences are unlikely to have a significant influence on the design of EP4. Second, if lenders had EP4-conform preferences already prior to EP4 (for instance, because they already adhere to strict climate risk assessments), this should already be reflected in their pre-EP4 lending. Our diff-in-diff estimate will hence provide us with an estimate of the incremental effect due to EP4. In this respect it is also useful to note that the decision to start the EP4-process was made already in October 2017, thus leaving three years until it became effective. Third, whereas a lender may decide to leave the EP once the plans for EP4 crystallize (and thus move to our control group), this is unlikely to occur due to reputational reasons. Departures are also very uncommon in practice (there are no departures at all before 2022, two years after the implementation of EP4) and the few that took place seem unrelated to the EP.[7] In addition, our result continues to hold if we exclude the few banks that left the EP from our analysis.

[7]For example, lenders leave because of mergers or because they are no longer active in the PF market. Credit Suisse merged with UBS and Eksport Kredit Fonden with Denmark's Export and Investment Fund, which resulted in two recent de-listings. The EPA further reports that voluntary de-listings in 2022 occurred because lenders were no longer active in the PF market (Equator Principles Association (2022)). In March 2024, after the end of our sample, JP Morgan, Citibank, Bank of America, and Wells Fargo left voluntarily. Reuters writes that this is driven by suggestions that environmental initiatives may breach antitrust rules and that all four banks will continue to be informed by the EP (https://www.reuters.com/business/finance/jpmorgan-citi-wells-boa-are-no-longer-signatories-equator-principles-website-2024-03-05/).

3 Data

3.1 Project Finance Syndicated Loans

We obtain all PF syndicated loans originated between the fourth quarter of 2015 and the third quarter of 2023 from DealScan.[8] Each deal contains one or more tranches that correspond to different products originated together in one deal (for example, two loan components with different maturities).

We remove deals with obvious mistakes in the data relevant for our analysis. These are cases where the number of lenders does not align with the actual lenders reported in a tranche, where different loan amounts are reported within a tranche or deal, where the tranche amounts do not (approximately) sum to the deal amount, or where the deal amount equals zero.

We impute and adjust data for lender shares and lender parent IDs. First, Lender shares are often missing or incorrect. For each tranche, we compute the lender share that is unaccounted for as 100 minus the sum of reported lender shares. When this is positive, we fill the lender shares of those lenders within the tranche without lender shares available to 100/n of the unaccounted share, where n is the number of lenders with missing lender shares. We scale the lender shares to 100 where the sum of the lender shares is between 99.5 and 100.5, as we assume that these are rounding errors. We filter out deals where lender shares do not add up to 100 after imputing and scaling. Those are deals with lender shares that are available but obviously wrong. Second, lender parent IDs are sometimes missing, in which case we fill them with the lender id. We manually check that this is reasonable by confirming that the lender parent name and the lender name are often the same in these cases.

We assign lead lenders following Acharya et al. (2020). Specifically, lenders with a role

[8] Specifically, tranche_o_a equals "Origination" and primary_purpose equals "Project Finance".

(either as primary or additional role) that includes "Agent", "Arranger", "Lead", or "Manager" are set to lead lenders. When this does not result in a lead lender, all lenders are assigned as lead. This second step mostly applies to sole lender deals and ensures that these lenders are properly identified as lead lenders.

We start with 6,952 project finance deals. After cleaning, the final sample consists of 6,029 deals involving 1,387 unique lenders. The average deal has a volume of 304 mln USD and 3 participating lenders.

3.2 Classifying the Greenness of Loans

PF is used to fund single-purpose developments, creating a direct link between the granting of a loan and a project. This allows measuring the environmental impact of the underlying project that is funded by a loan. We use two different approaches to classifying projects. The first approach limits the sample to energy projects and classifies deals as fossil fuel or renewable energy projects based on a simple keyword search. Second, we use OpenAI's large language model GPT-4 to classify projects. Both approaches exploit information in the DealScan project description (in the deal and purpose remarks) together with industry identifiers and the name of the parent company provided.[9]

For the first classification using energy projects only, we first select projects based on the energy industry identifiers.[10] This sub-sample includes 4,351 of the 6,029 projects in our sample. Within this sub-sample, we search for keywords from a list of words related to

[9] All from DealScan: Broad industry group, major industry group, SIC, NAICS, Project Finance industry ('project_finance'), loan purpose and deal remark.

[10] We select projects where the DealScan industry identifier 'project_finance' equals one of: Electric/Other, Electric/Cogeneration/Coal-fired, Gas/Oil Processing, Gas/Oil Field Development, Gas/Oil Storage, Electric/Cogeneration/Technology N/A, Electric/Independent/Coal-fired, Electric/Independent/Gas-fired, Electric/Geothermal, MTBE Plants, Electricity transmission, Electric/Hydroelectric, Electric/Cogeneration/Gas-fired, Electric/Independent/Technology N/A, and Pipelines.

renewable or fossil fuel energy, respectively.[11] We then classify projects as renewable or fossil fuel if they *only* match words from the corresponding list, resulting in 3,376 classifications.[12] Of the 72 projects with keywords from both lists, we can manually classify 49 (an example of such a case is a solar farm constructed on an area formerly used for coal mining). We leave the remaining unclassified, and we do the same for projects without any keyword match. We ultimately end up with 3,425 classified projects (about 79% of the energy projects and 57% of all projects in our sample).

Keyword-based classification works well for the energy projects. However, other projects are harder to classify in that way because there are many dimensions in which a project can be green or brown. Therefore, our second classification uses OpenAI's large language model GPT-4. We design a prompt that instructs GPT to evaluate a project's environmental impact based on the provided information and classify the project as green, neutral, or brown (Appendix A.2 provides the exact prompt).

This approach enables us to better exploit the unstructured textual project descriptions and classify the full sample of projects. However, a concern with this approach is that it can lead to a noisier classification. We implement several checks to alleviate this concern as much as possible. First, we ask GPT to provide a motivation and a certainty score for each classification. Requesting a motivation forces the model to use consistent "reasoning" for classification.[13] We remove deals where the model returns zero certainty (those are typically

[11] We include the following keywords. Renewables: renewable, solar, photovoltaic, PV, wind, biomass, thermosolar, geothermal, hydro, agrivoltaic, bioenergy, biofuel, biogas. Fossil: gas, petro, oil, LNG, coal, gasification, lignite, crude.

[12] To confirm that these are indeed renewable or fossil energy projects, we manually check 50 from each category. Of these, 49 renewable and 48 fossil energy projects are unambiguously correctly classified. We observe one loan that is used to construct a warehouse for a company that sells solar panels, classified as renewable energy. We further observe two projects that are ambiguously classified as fossil energy. One deal is about a peat-fired project, which is not formally a fossil fuel, but also results in high carbon emissions. Another is a petrol refinery but the project loan is used to make this refinery greener. Overall, the measurement error in this classification appears small.

[13] These motivations align well with the actual classification. Examples are "Telecommunications, no direct environmental impact" for a neutral deal and "Anaerobic digestion plant, waste to energy" for a green deal.

cases that are hard to classify, such as a deal to refinance a previous loan). Second, we feed GPT the prompt together with batches of 50 deals at a time via the OpenAI API. The advantage of feeding several deals at a time is that deals are evaluated in a larger context. To ensure the context is similar across batches, we randomize deals into batches.

Third, we reduce noise and make the output as replicable as possible by fixing the seed and switching off "creativity" by setting the "temperature" parameter equal to zero.[14] Nevertheless, some residual random variation in output from the model remains. Therefore, we run the entire evaluation five times and compare the outcomes across these iterations. Reassuringly, the classifications from different iterations overlap reasonably well. For the subsample of energy deals, all GPT iterations are similarly accurate and assign the same classification as assigned in the keyword-based classification around 95% of the time. The iterations also overlap in the broader sample that includes all PF deals. Table 8 Panel A in Appendix A.2 shows that the iterations all result in similar amounts of green, neutral, and brown classifications. Panels B to D show that the dummies for green, neutral, and brown classifications are highly correlated across these iterations (specifically, the correlations for the green dummy are in the range of 0.9 to 0.95).

Our loan-level analysis uses the loan classification as outcome variables. For the lender-level analysis, we aggregate each loan category (green, neutral, brown) at the lender-year level. Observations from the fourth quarter of year t until the third quarter of year $t+1$ are assigned to the same year to match the treatment timing (EP4 was implemented in Q4).[15] For each lender-year, we calculate the ratio of the number of green, brown, and neutral to total deals, respectively (*deals ratio*). We also calculate the same ratios weighted by deal value (*value ratio*). For the energy sub-sample, we construct these ratios based on renewable

[14] The temperature parameter controls the randomness in GPT output. A higher temperature implies the model is more likely to produce different output given the same prompt.

[15] As an example, the observations in period $t = 0$ contain a full year starting at the implementation of EP4. Thus, since EP4 is implemented at the beginning of 2020Q4, the data from 2020Q4 until the end of 2021Q3 is included in this period.

to total renewable and fossil fuel deals.

3.3 Equator Principles

We obtain a list of members of the EP Association (EPA) from the EP website, including their join date.[16] We manually select the lender parent IDs in Dealscan that match these lenders based on the lender names.

3.4 Descriptive Statistics

Figure 1 provides information on the importance of project types by year. Panel A shows that projects are often related to energy and infrastructure, illustrating the importance of PF for the green transition. Energy accounts for more than sixty percent of the market in most years. Panel B shows that energy deals are usually green or brown (neutral deals are below 10% in most years). Earlier research suggested that the PF market is a large part of renewable energy financing (for example, in 2015, more than half of the new renewable energy projects is financed through PF instead of corporate loans (Steffen, 2018)). We observe a similar amount of brown energy financing. Panel B also shows that, in contrast, infrastructure projects are often classified as neutral (more than 50% in most years), consistent with such projects often having neither a clear negative nor positive environmental impact.

Table 2 shows the descriptive statistics at both the lender-year level and the loan level in Panels A and B, respectively. Most lender-year observations are control lenders, but treated lenders are larger, which explains that 60% of the loans are treated in Panel B. Treated and control lenders do not differ much in their average greenness over the sample; the mean ratios are very similar. Treated loans do not differ from control loans in greenness, but they are larger and have shorter maturities.

[16]The most recent list of EP members is available at https://equator-principles.com/epfis-reporting/. Our analysis is based on the information available on Dec 31, 2023.

Figure 2 shows that the PF market is very skewed towards large lenders. In order to avoid our analysis being disproportionately influenced by small lenders that do not affect the market much, we use a weighted regression (using the number of deals in a lender-year) for our lender-level analyses.

4 Lender-Level Analyses

In this section, we focus on the greenness of lender portfolios by running Difference-in-Differences analyses around the introduction of EP4. We examine whether post-EP4, EP members finance more renewable energy deals in the renewables and fossil energy sub-sample, and more broadly green, neutral, or brown projects based on the classification by GPT in the full sample.

4.1 Benchmark Results: Lender-Level Difference-in-Differences

We estimate the following regression specification:

$$Ratio_{i,c,t} = \alpha_i + \gamma_{c,t} + \beta Treat_i \times PostEP4_t + \epsilon_{i,c,t}, \tag{1}$$

where $Ratio_{i,c,t}$ is the ratio of renewable to total renewable and fossil fuel energy deals or, more broadly, green, neutral or brown to total deals for lender i in country c at time t. We consider two versions of $Ratio_{i,c,t}$: *deals ratio* is computed based on the number of deals a lender is involved in, and *value ratio* weights the deals by value. α_i and $\gamma_{c,t}$ are lender and lender country $\times$ time fixed effects that control for time-invariant lender characteristics and time-varying differences between lender countries. Treat equals 1 when lender i is an EP member prior to the implementation of EP4, and 0 otherwise.[17] Post is 1 from October

[17]We drop lenders from our analysis that joined the EP after the implementation of EP4. If we include these lenders (either as treated or as control) the results remain qualitatively and quantitatively the same.

2020, the start date of EP4. β is the key DiD coefficient of interest, which measures whether treated lenders move from fossil fuels to renewable energy or to green, neutral, or brown lending after EP4. We cluster standard errors at the lender and time dimensions and weigh each observation by the number of deals by a lender in a year.

Table 3 reports the results from these regressions. These regressions show no evidence supporting our hypothesis that treated lenders originate fewer brown loans after EP4. In column (1), the dependent variable is the *renewables deals ratio*, the number of renewable energy deals to the total of renewable and fossil energy deals a lender is involved in. Column (2) replaces this variable by the value-weighted version *renewables value ratio*. In both columns, the coefficient estimate on the interaction term $Treat \times Post\ EP4$ is statistically insignificant. Importantly, the estimated coefficients are also quantitatively small and they flip signs between specifications.

Columns (3)–(8) of Table 3 present similar results for the full sample using the GPT-based classification. In columns (3)–(4), we examine green lending. The coefficient estimates are negative and statistically insignificant. In columns (5)–(6), we consider neutral deals and find a positive but statistically insignificant coefficient estimate. In columns (7)–(8), we analyze brown lending. We again find statistically insignificant coefficients that are quantitatively small and flip signs between the specifications. The results for the green and brown ratios remain quantitatively and qualitatively similar when we drop neutral loans, which could potentially confound the treatment impact on green and brown deal and value ratios (see the additional results in Panel A of Table 10 of Appendix A.3). Overall, if anything, there is a small and statistically insignificant shift away from green towards neutral deals, inconsistent with the hypothesis that EP4 results in a reduction in brown lending.

To assess the statistical power of our tests, we follow Bloom (1995) and compute the minimum detectable effect size (MDES) that can be detected with 80% probability at a 10% significance level. We focus the discussion on our key outcome variables: brown lending ratios

in Columns (7) and (8), and renewables lending ratios in Columns (1) and (2). In Columns (7) and (8), the MDES is approximately one-seventh and one-eight of a standard deviation of the dependent variable, respectively.[18] Thus, these tests are reasonably well-powered as they allow us to detect an effect that is a fraction of a standard deviation of the brown lending ratios. In Columns (1) and (2), we compute an MDES of roughly one-third of a standard deviation of the respective renewables ratio. Thus, the statistical power in these tests is somewhat lower due to the smaller sample size using the renewables/fossil fuel keyword classification. This highlights a caveat in interpreting results based on the renewables ratios and underscores the importance of complementing the keyword-based classification with the GPT-based classification.

Collectively, the results based on different classifications paint a consistent picture. The introduction of EP4 did not lead EP members to shift lending to more environmentally friendly projects compared to non-members.[19] In the remainder of this section, we focus on the GPT-based classification, which enables us to use the full sample and greater statistical power. The results based on the energy sub-sample are reported in Appendix A.3 Figure 8.

4.2 Parallel Trends

Our main coefficient may be biased towards zero if pre-trends are present that offset the treatment effect. We now examine the parallel trend assumption, by estimating a dynamic DiD with separate coefficients for each period before and after EP4, dropping period -1. Figure 3 presents the results. While some pre-treatment coefficients are statistically different from zero, there are no clear pre-trends. The only notable effect is in period $+1$, with a spike in neutral value and a decrease in green value (mirroring the insignificant shift from green to

[18] At a power level of 80% and significance level of 10%, the MDES is computed as $2.49 \times SE$, where SE is the standard error of the coefficient estimate. For more details, see Bloom (1995).

[19] Note that a reallocation of funding from members to non-members cannot explain the null result. In this case, we would expect sponsors of brown projects to switch from member to non-member lenders which would result in lower green shares for members

neutral deals estimated in Table 3). However, this is a single observation and goes against the direction that one would expect if the implementation of climate risk management in EP4 resulted in a reduction in brown lending. Overall, the graphs reaffirm prior estimation results, giving no indication that EP4 affects the greenness of credit allocation.

4.3 Robustness

We investigate many variations of the main regressions to examine whether our results are driven by a specific model specification. Specifically, we identify six important modeling choices for which reasonable alternatives are available and examine robustness regarding them:

1. EP leavers. In the benchmark setting, all lenders that join the EP before EP4 are defined as treated. Lenders that join after EP4 are removed from the sample, and all others are control lenders. As alternative, we additionally drop lenders that leave the EP in 2022 or 2023 from the sample.

2. Treatment definition. All lenders that join the EP before EP4 are treated in the benchmark setting. Alternatively, we only classify lenders that joined at least two years before EP4 as treated.

3. Fixed effects. The benchmark includes lender and lender country $\times$ time. We consider three alternatives: lender and lender region $\times$ time; lender, lender size bucket $\times$ time, and lender country $\times$ time; lender, lender size bucket $\times$ times, and lender region $\times$ time. In DealScan, a region is a broader geographical area than a country, e.g. Western Europe.

4. Frequency. The main analysis is on data aggregated by year. As an alternative, we consider quarterly data.

5. GPT iteration. As discussed in Section 3.2, the greenness classifications differ slightly with different iterations of GPT. The benchmark uses the first version we ran. As alternative, we run four different iterations.

6. Lender size filters. As previously discussed, the PF market is highly skewed (there are a few large and many small lenders). To avoid over-weighting small lenders, the benchmark setting runs a weighted regression including all lenders, with weights based on the number of deals that a lender is involved with in a period. We include two alternatives: a weighted regression including all lenders with weights based on the log(1 + number of deals), and an unweighted regression. In the unweighted regression, we exclude very small lenders with at least ten deals in the four years pre-sample to avoid including lenders that do not tend to do at least a PF deal a year. Both alternatives give more weight to small lenders.

In a first step, we consider single deviations from the baseline model, while keeping all other modeling choices as in the baseline setting. In total, there are 13 specifications for each outcome variable, corresponding to 78 specifications that we implement for all six outcome variables as in our benchmark settings in Table 3. We report the coefficient estimate on the interaction term $Treat \times Post\ EP4$ together with its t-statistic in a scatter plot in Figure 4. As in our benchmark setting, the coefficient estimates are mostly statistically insignificant and the estimate from our benchmark specification is often in the middle of the range of estimates. Out of the 78 specifications, only three are statistically significant at the 5% level. These statistically significant results show an increase in the neutral deals ratio (see Panel C).

In Figure 4 we restrict the number of model specifications to 78 to clearly illustrate the effects of deviations from our benchmark model. We now take a step further by testing all combinations of the potential modeling choices listed above. In total, this gives us $2 \times 2 \times 4 \times 2 \times 5 \times 3 = 480$ specifications that we select for each outcome variable (i.e., a total of

2880 specifications). Figure 5 plots the densities of the coefficient estimates and t-statistics using all these alternative DiD specifications. These densities are roughly centered around zero. For the green deals ratios, none of the estimates are statistically different from zero. The neutral and brown deal ratio estimates are also mostly statistically insignificant, but the mean for the neutral ratios is slightly above zero, and the mean for brown is slightly negative, with some statistically significant estimates. If these significant estimates were the true effect, they would indicate a shift in lending from brown to neutral projects in response to EP4. Accordingly, we investigate the negative and statistically significant estimates for the brown deals ratios in more depth.

Small vs Large Lenders. Examining the set of negative coefficient estimates for the brown ratios, we find that the majority of the statistically significant and economically large estimates stem from specifications in which we do not weight observations by lender size. In these specifications, smaller lenders have a relatively larger weight compared to our baseline regressions. This suggests that there may be a reduction in brown lending by EP members in response to EP4, but only among small lenders that do not contribute significantly to aggregate lending volumes.

To investigate this conjecture, we re-run our baseline specifications splitting the sample into small and large lenders, splitting by median lender size based on the number of PF deals that a lender is involved with in a lender $\times$ year. Due to the high skewness in the size distribution (see Figure 2), below-median-size lenders only cover 9% of the total deal value in our sample. We then re-estimate Specification (1) but do not apply weights by lender size and include a triple interaction term $Treat \times Post\ EP4 \times Size\ Dummy$. We only include lenders involved with at least ten deals in the four years pre-sample to ensure that lenders in the sample are active in most years. Table 4 reports the results. Among small lenders, there is indeed a significant decline in brown lending. According to our estimates, small

EP members decrease their brown deals (value) ratio by 21.62% (15.76%) relative to small non-members post-EP4. By contrast, among large EP members, we find small positive point estimates that are statistically indistinguishable from zero. We repeat this exercise splitting the sample into size quintiles. The point estimates plotted in Figure 6 show that the decline in lending to brown projects is concentrated in the smallest quintile of lenders, jointly responsible for 1% of the lending volume in our sample.

These findings indicate that EP4 resulted in a shift to greener lending, but only among the smallest lenders which contribute little to aggregate lending volumes. This explains why we find an overall null result in our baseline specification, which applies weights based on lender size, and highlights the importance of considering lender size when assessing aggregate effects—especially in the context of climate change, where aggregate emissions are the most relevant outcome. Economically, the results are consistent with small lenders having weaker climate risk management before EP4 or with the costs of compliance with the climate risk requirements being relatively larger for small lenders.

Taken together, our analysis based on 480 different specifications for each independent variable indicates that, irrespective of modeling choices, we cannot detect a consistently significant effect of EP4 on green, brown, or neutral lending, except among the smallest lenders that do not impact aggregate lending volumes to brown projects much. Overall, the estimates show that our null findings are not chance or cherry-picked outcomes; they are robust not only to common one-directional robustness tests but also to model risk or non-standard errors (Menkveld et al., 2024).

5 Loan-Level Analyses

The lender-level regressions show that EP members do not make more green loans after EP4 compared to non-members. However, this could be due to confounding changes in demand

for specific project types faced by EP members. In this section, we control for these effects by moving to the loan level.

5.1 Loan-Level Difference-in-Differences

We apply a loan-level DiD design to test whether the share of renewable energy projects within the sub-sample of renewable and fossil energy projects changes, or the share of non-brown versus brown projects within all treated loans after EP4. We estimate the following regression specification:

$$Greenness_{j,t} = FE_{j,t} + \beta Treat_j \times PostEP4_t + \epsilon_{j,t}, \tag{2}$$

where $Greenness_{j,t}$ is a dummy for whether a project j funded in quarter t is renewable energy or non-brown, respectively. The renewables dummy is used in the sub-sample analysis of renewable and fossil energy projects. It equals 1 for renewable energy loans and 0 for fossil fuel energy loans. The non-brown dummy is used in the full sample and equals 1 for green or neutral loans and 0 for brown loans. $Treat$ is 1 when a loan is at least 10 mln USD and an EP member is part of the consortium.[20] Post is 1 from October 2020, with the start date of EP4. We include a range of different fixed effects, which we abbreviate as $FE_{j,t}$ in the equation above. We combine versions of lender, time, and industry $\times$ location $\times$ size $\times$ time (ILST). These control for time-invariant lender characteristics, time-varying market conditions, and demand effects (Degryse et al., 2019). Location fixed effects are based on the project country and size fixed effects are based on size buckets after sorting the loans in each quarter into size quintiles. Industry fixed effects are based on SIC-2 industry codes. There are 67 industries and there is sufficient variation in project greenness within industries. For example, SIC code 49 "Electric, Gas and Sanitary Services" is the largest

[20] We do not use a loan size cutoff to define treatment because only 229 out of 6,029 loans are smaller than 10 mln USD.

industry and contains fossil fuel plants as well as solar and wind power plants. Note that the loan-level estimation is consistent with our previous lender-level analysis where observations are weighted according to lender-deals.

Table 5 presents the results. In Panel A, we focus on the sub-sample of renewable and fossil fuel energy projects. We find that the share of renewable energy projects does not increase after EP4. The DiD coefficients of interest are always statistically insignificant, small in absolute terms, and range from positive to negative depending on the specification. Controlling for demand effects does not change our conclusion. The coefficient of interest remains negligible in the most stringent specification presented in column (6), where we control for ILST fixed effects to eliminate time-variation in demand, based on the assumption that projects in the same industry, country, size, and time have similar funding demand.

We consider the full sample using the GPT-based project classification in Panel B of Table 5. We find similar results with slightly smaller standard errors due to the increased statistical power. The share of non-brown projects does not increase after EP4. As in Panel A, the coefficients of interest are all small and range from positive to negative. The largest absolute coefficient is in the specification in column (6), which controls for ILST fixed effects. While statistically insignificant, the negative coefficient estimate in this specification indicates that, if anything, EP lenders *increase* brown lending after EP4, inconsistent with EP4 resulting in a shift away from brown lending.[21] Overall, given the low statistical significance and flipping of signs across columns, we conclude that the share of non-brown loans is not affected by EP4.

To assess the statistical power of the tests, we again compute the MDES, focusing on the specifications with the richest set of fixed effects in Columns (5) and (6). In Column (5), the MDES is around one-seventh of a standard deviation of the renewables dummy in

[21] We again confirm that neutral loans do not confound the impact of EP4 on brown and green loans by replicating the analysis from Table 5 Panel B on a smaller sample where we drop neutral deals. These results are available in Table 10 in Appendix A.3 and similar to the original results in Table 5.

Panel A, and around one-eight of a standard deviation of the non-brown dummy in Panel B. Thus, these test are reasonably well powered. In Column (6), the inclusion of very narrow fixed effects results in relatively large standard errors and, consequently, weaker statistical power: the MDES is around a quarter of the standard deviation of the respective dependent variable. This is an important caveat in interpreting the results. At the same time, we note that in these specifications the point estimate is negative, inconsistent with a shift to greener lending.

5.2 Loan-Level Triple-Differences

Even if the propensity to originate a non-brown loan does not increase after EP4, it may be that lenders change the characteristics of such loans. For example, they may issue them with larger sizes or longer maturities compared to brown loans. This aligns with the findings of Ivanov et al. (2023) who show that brown firms receive less bank financing and shorter maturity loans after firms are subject to a carbon pricing policy. We investigate this question using a triple-difference design. We focus on the full sample using the GPT-based project classification for the remainder of this section. The regression specification is as follows:

$$Y_{j,t} = FE_{j,t} + \beta Treat_j \times PostEP4_t \times Non - Brown_{j,t} + \epsilon_{j,t}, \tag{3}$$

where Y is either the log of the deal value in million USD or the loan maturity in months. When the deal includes multiple loans, the maturity used is the value-weighted average of the loan maturity in each tranche. We include the same range of fixed effects and treatment definitions as in Equation (2).

Table 6 shows the results for these triple differences, separately for loan size and loan maturity in Panels A and B, respectively. In both panels, we observe statistically insignificant coefficients for all specifications. Also from this angle, EP4 does not have a differential impact

on brown versus non-brown loans.

We note that both of these test have relatively wide standard errors, and consequently, they are weakly powered. However, as we discuss below, when we consider a range of model specifications, the coefficient estimates across model specifications are centered around zero, and we find roughly as many positive as negative coefficient estimates. Thus, while the statistical power of these tests is limited, the changing signs of the coefficient estimates indicate it is unlikely that there is a positive effect on the size of loans to non-brown projects that we are unable to detect due to limited power.

Next to size and maturity, non-brown loans may receive lower rates compared to brown loans. This may be the case because the cost of complying with EP4 may be linked to the rates charged to brown PF loans. Unfortunately, pricing data is missing for most PF syndicated loans in DealScan. The sample of loans for which these data is available is too small to analyze meaningfully.

5.3 Robustness

For each of the results for the subsample of renewable and fossil fuel energy loans in columns (2) to (6) of Table 5 Panel A we run the same analysis once more with three different treatment definitions. In the benchmark setting, a loan is treated when there is EP member involvement and the loan is larger than 10 million USD. Alternatively, we use treatment intensities based on the share of lenders or lead lenders that is part of the EP. Together with the different fixed effects options already included above, there are 15 specifications for this DiD. We implement the same robustness tests for the DiD and triple differences results on the full sample of loans (columns (2) to (6) of Table 5 Panel B and Table 6), where we additionally include five different greenness classifications from the GPT model. Thus, for these analyses, we report the results from a total of 75 alternative specifications. The coefficients of interest and the corresponding t-statistics for these robustness tests are

presented in Figure 7. The null results in the loan-level output are robust to these variations in modeling choices. The point estimates from the different specifications are relatively evenly split around zero, with roughly as many positive as negative estimates. Therefore, we are unable to find a robustly positive or robustly negative effect, consistent with a null result.

6 Cross-Country Heterogeneity

The results so far indicate that the implementation of EP4 has not affected the greenness of loan origination on average globally. However, EP4 may still have shifted lending in specific locations where its incremental effect is expected to be most pronounced. We consider two such subsamples. First, we hypothesize that lenders outside of the EU are more affected by the requirements in EP4 than EU lenders because the European Central Bank has a stricter stance on climate risk than other banking supervisors. Therefore, we run the lender-level DiD analysis from Equation (1) for the subsample of non-EU lenders. Second, we hypothesize that loans to projects in non-designated countries are more affected by EP4. The EP define designated countries as OECD countries on the World Bank High-Income list, and the EP are generally more stringent for loans to projects in non-designated countries. Therefore, we run the loan-level DiD analysis from Equation (2) for this subsample of loans.

Table 7 presents the results. Panel A shows results from the lender-level analysis on non-EU lenders. Here, we cannot reject the null hypothesis for any of these tests. If anything, the coefficients indicate a move from green to neutral and brown lending, which goes against our hypothesis. However, we do not wish to overinterpret these results since all coefficients are statistically not distinguishable from zero. Panel B shows the results from loan-level analysis on loans to projects in non-designated countries. We find larger coefficients than in the main loan-level analysis from Table 5. Coefficients are positive and partially significant in

columns (1)-(4). Once we control for industry x time fixed effects, they become smaller and insignificant, suggesting a reallocation of lending across industries over time, independent of EP membership. Overall, across both subsample analyses, we do not find robust and consistent evidence to indicate that the greenness of loan origination is affected by the implementation of EP4.

7 Conclusion

Many lenders join voluntary initiatives that promote environmentally responsible lending. It is important to understand whether such initiatives result in greener loan origination. We analyze this question in the project finance (PF) market, which is highly relevant for the green transition. PF allows us to measure the environmental impact of the funded expenditures relatively cleanly because loans support single-purpose developments. A specific (incremental) project that is funded through a new loan is often not observed in other settings.

Our analysis focuses on the Equator Principles (EP), the main green initiative in the PF market. We analyze the impact of EP4, a tightening of the EP that introduces requirements for climate risk assessments of newly originated PF loans. Using two alternative classifications of the greenness of a project, we do not find that EP members change the greenness of their lending following the introduction of EP4, except for the subgroup of small EP members. We find that small EP members move away from brown PF lending after EP4 compared to small non-members. However, these results are concentrated in the quintile of the smallest lenders which jointly do not impact aggregate PF lending. The results are robust to a wide range of alternative modeling specifications, and to analyzing the impact of EP4 at the loan level. Similarly, there is no evidence that the characteristics of green projects change post-EP4, such as through longer maturities and higher lending volumes.

There is also no evidence for cross-country heterogeneity in EP4 impact: EP4 does not seem to affect subgroups of lenders or loans in geographies for which one may conjecture EP4 to have the highest incremental effect. Overall, our results indicate that the introduction of EP4 did not lead to a shift away from brown PF lending activity.

As our results are unlikely to be explained by data and modeling choices, they speak towards the ineffectiveness of voluntary green initiatives. Our results thus provide a cautionary note towards relying on voluntary initiatives in supporting a swift transition towards a green economy.

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Table 1: Reference to Sustainability Initiatives in Bank Reports

This table reports the attention given to sustainable initiatives in the sustainability and annual reports of the top 25 banks based on the value of their 2022 syndicated loan origination. The table shows how many of these 25 banks are members of each initiative by the end of 2022. It further shows the percentage of these banks that mention a specific initiative at least once (Mention Rate) and the total number of times they are mentioned by all banks (Mentions) for each year and report type. When a bank does not have an explicit ESG report, we include the annual report in this analysis such that all output below is based on all 25 banks. We include four initiatives focused on action: the Equator Principles (EP), the Net-Zero Banking Alliance (NZBA), the Principles for Responsible Banking (PRB), and the Science Based Targets initiative (SBTi). We also include two initiatives focused on disclosure: the Task Force on Climate-related Financial Disclosures (TCFD) and the Carbon Disclosure Project (CDP). Details about the included banks, their reports, and the methodology behind these numbers are available in Appendix A.1.

	Action				**Disclosure**	
Membership	EP	NZBA	PRB	SBTi	TCFD	CDP
Banks (N)	19	21	14	7	3	24
ESG Report	EP	NZBA	PRB	SBTi	TCFD	CDP
2022 Mention Rate	72%	68%	36%	36%	88%	60%
2022 Mentions	395	231	197	44	601	108
Annual Reports	EP	NZBA	PRB	SBTi	TCFD	CDP
2019 Mention Rate	44%	0%	32%	8%	68%	28%
2020 Mention Rate	40%	0%	32%	12%	68%	40%
2021 Mention Rate	44%	64%	28%	28%	84%	48%
2022 Mention Rate	44%	64%	28%	28%	72%	24%
2019 Mentions	77	0	52	4	94	24
2020 Mentions	73	0	42	3	130	22
2021 Mentions	82	90	38	19	179	38
2022 Mentions	74	107	52	17	261	30

Table 2: Descriptive Statistics

This table reports descriptive statistics at the lender x year level and the loan level in Panels A and B, respectively. We show them separately for treated and control lenders and loans. EP member is 1 if the lender is an EP member in that lender x year. Post EP4 is 1 after 2020Q4. Ratios are the sum of renewable to total renewable and fossil fuel energy deals, or broader green, neutral, or brown deals or deal value in a lender x year divided by the total numbers of deals or deal value in that lender x year. The renewable dummy is 1 for renewable, 0 for fossil energy project. Non-brown is 1 for green and neutral deals, 0 for brown deals. Maturity is the average maturity of the tranches in a loan, weighted by tranche size. The sample starts in 2015 Q4 and ends in 2023 Q3. Annualized data for lenders combines the data from year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.

Panel A: Descriptive Statistics on the Lender x Year-Level

			Treat				Control			
	Unit	Level	n	Mean	Median	SD	n	Mean	Median	SD
EP member	Dummy	Lender x Year	631	0.930	1.000	0.255	3061	0.000	0.000	0.000
Post EP4	Dummy	Lender x Year	631	0.377	0.000	0.485	3061	0.343	0.000	0.475
Number of deals	n	Lender x Year	631	15.513	7.000	21.947	3061	2.851	1.000	4.261
Renew deals ratio	[0-1]	Lender x Year	560	0.662	0.716	0.331	2009	0.676	1.000	0.435
Renew value ratio	[0-1]	Lender x Year	560	0.613	0.649	0.361	2009	0.660	1.000	0.447
Green deals ratio	[0-1]	Lender x Year	631	0.436	0.455	0.298	3061	0.438	0.333	0.437
Green value ratio	[0-1]	Lender x Year	631	0.400	0.364	0.318	3061	0.419	0.228	0.444
Neutr deals ratio	[0-1]	Lender x Year	631	0.245	0.200	0.254	3061	0.222	0.000	0.360
Neutr value ratio	[0-1]	Lender x Year	631	0.241	0.169	0.271	3061	0.225	0.000	0.370
Brown deals ratio	[0-1]	Lender x Year	631	0.319	0.286	0.284	3061	0.340	0.000	0.420
Brown value ratio	[0-1]	Lender x Year	631	0.360	0.337	0.314	3061	0.356	0.000	0.434

Panel B: Descriptive Statistics on the Loan-Level

			Treat				Control			
	Unit	Level	n	Mean	Median	SD	n	Mean	Median	SD
Treat intensity	[0-1]	Loan	3606	0.722	0.750	0.275	2423	0.000	0.000	0.000
Treat lead intensity	[0-1]	Loan	3606	0.768	0.889	0.272	2423	0.000	0.000	0.000
Renewable	Dummy	Loan	2091	0.800	1.000	0.400	1334	0.865	1.000	0.342
Non-brown	Dummy	Loan	3606	0.781	1.000	0.413	2423	0.802	1.000	0.398
Post EP4	Dummy	Loan	3606	0.357	0.000	0.479	2423	0.328	0.000	0.469
log(value)	log($mn)	Loan	3606	5.058	5.049	1.257	2423	4.198	4.169	1.451
Maturity	Month	Loan	3019	119.734	94.000	79.699	1376	157.705	175.000	82.120

Table 3: Difference-in-Differences for Lender-Level Greenness Ratios

This table shows the results from a difference-in-differences analysis on the greenness of EP lenders after the introduction of EP4, based on Specification (1). In the first two columns, we restrict the sample to renewable and fossil energy projects. The outcome variable is the ratio of renewables deals or deal value to the total deals or deal value in the restricted sample. In the remaining columns, all projects are included to analyze the ratio of green, neutral, or brown deals or deal value to total deals or deal value in a lender x year. We regress the respective ratio on Treat $\times$ Post EP4 and include fixed effects for Lender and Lender Country $\times$ Time. Standard errors are two-way clustered at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.

	Renewables Ratios		Green Ratios		Neutral Ratios		Brown Ratios	
	Deals	Value	Deals	Value	Deals	Value	Deals	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat $\times$ Post EP4	0.0168	-0.0039	-0.0211	-0.0490	0.0279	0.0408	-0.0068	0.0082
	(0.0516)	(0.0553)	(0.0349)	(0.0443)	(0.0219)	(0.0414)	(0.0253)	(0.0204)
Fixed-effects								
Lender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Country x Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,569	2,569	3,692	3,692	3,692	3,692	3,692	3,692
R^2	0.80	0.79	0.75	0.71	0.67	0.65	0.75	0.73

*Clustered (Lender and Time) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 4: Triple-Differences for Lender-Level Greenness Ratios

This table shows the results from splitting the baseline difference-in-differences analysis by lender size, by including a triple-difference term $Treat \times Post\ EP4 \times Size\ Dummy$ to Specification (1), and using unweighted regression. We only include lenders involved with at least ten deals in the four years pre-sample. The outcome variable is the ratio of green, neutral, or brown deals or deal value to total deals or deal value in a Lender × Year. We include fixed effects for Lender and Lender Country × Time and controls for all single and two-way combinations of $Treat$, $Post\ EP4$, and $Size\ Dummy$. Standard errors are two-way clustered at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. Large (Small) is 1 (0) if the lender is above-median size based on the number of deals in that Lender × Year observation, and 0 (1) otherwise. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.

	Green Ratios		Neutral Ratios		Brown Ratios	
	Deals	Value	Deals	Value	Deals	Value
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post EP4 × Small	0.1626*	0.1352*	0.0536	0.0224	-0.2162***	-0.1576***
	(0.0820)	(0.0578)	(0.0759)	(0.0751)	(0.0392)	(0.0370)
Treat × Post EP4 × Large	0.0006	-0.0270	-0.0076	0.0062	0.0071	0.0209
	(0.0369)	(0.0446)	(0.0266)	(0.0365)	(0.0386)	(0.0599)
Fixed-effects and controls						
Lender	Yes	Yes	Yes	Yes	Yes	Yes
Lender Country × Time	Yes	Yes	Yes	Yes	Yes	Yes
Controls for underlying interactions	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,028	1,028	1,028	1,028	1,028	1,028
R^2	0.71	0.67	0.52	0.51	0.68	0.65

*Clustered (Lender and Time) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 5: Difference-in-Differences for Loan-Level Greenness

This table shows the results from a difference-in-differences analysis on the greenness of loans after the introduction of EP4. In Panel A, we restrict the sample to renewable and fossil energy projects. The outcome variable is the renewables dummy which equals 1 for renewable energy projects, 0 for fossil energy projects. In Panel B, we include the full sample and the outcome variable is the non-brown dummy which equals 1 for green or neutral projects and 0 for brown projects. We regress the respective loan level dummies on the treatment by EP4, Treat × Post EP4. We include combinations of fixed effects for Lender, Time, Country, Industry (2-digit SIC) and size (quintile size buckets). Treat is set to 1 when the loan is both larger than 10 mln USD and has EP member involvement, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. The sample uses quarterly loan level data and starts in 2015Q4 and ends in 2023Q3.

Panel A: Sample of Renewable and Fossil Energy Projects

	Renewables dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post EP4	0.0094	-0.0142	-0.0136	0.0179	-0.0148	-0.0073
	(0.0280)	(0.0268)	(0.0269)	(0.0348)	(0.0235)	(0.0408)
Fixed-effects						
Lender		Yes	Yes	Yes	Yes	Yes
Year x Quarter			Yes			
Year x Quarter x Country				Yes		
Year x Quarter x Industry					Yes	
Year x Quarter x Country x Industry x Size						Yes
Observations	3,425	3,425	3,425	3,425	3,397	3,397
R^2	0.01	0.50	0.51	0.76	0.69	0.94

Panel B: Full Sample

	Non-Brown dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post EP4	0.0355	0.0180	0.0174	0.0231	0.0043	-0.0471
	(0.0226)	(0.0227)	(0.0228)	(0.0302)	(0.0214)	(0.0385)
Fixed-effects						
Lender		Yes	Yes	Yes	Yes	Yes
Year x Quarter			Yes			
Year x Quarter x Country				Yes		
Year x Quarter x Industry					Yes	
Year x Quarter x Country x Industry x Size						Yes
Observations	6,029	6,029	6,029	6,029	5,967	5,967
R^2	0.00	0.36	0.37	0.60	0.63	0.93

*IID standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 6: Triple-Differences for Loan-Level Size and Maturity

This table shows the results from a triple-difference analyses on the size and maturity of non-brown versus brown loans after the introduction of EP4 in Panels A and B, respectively. We regress the loan size (log(value in mln USD)) or maturity (in months) on Treat × Post EP4 × non-Brown. We include combinations of fixed effects for Lender, Time, Country, Industry (2-digit SIC) and size (quintile size buckets). Treat is set to 1 when the loan is both larger than 10 mln USD and has EP member involvement, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. The non-Brown dummy is 1 for green or neutral deals, 0 for brown deals. The sample uses quarterly loan level data and starts in 2015Q4 and ends in 2023Q3.

Panel A: Loan Size

	log(value)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post EP4 x non-Brown	0.1116	0.0812	0.0760	0.1659	0.2251	0.2096
	(0.1780)	(0.1646)	(0.1645)	(0.2004)	(0.1960)	(0.2093)
Fixed-effects						
Lender		Yes	Yes	Yes	Yes	Yes
Year x Quarter			Yes			
Year x Quarter x Country				Yes		
Year x Quarter x Industry					Yes	
Year x Quarter x Country x Industry x Size						Yes
Observations	6,029	6,029	6,029	6,029	5,967	5,967
R^2	0.17	0.55	0.56	0.73	0.65	0.98

Panel B: Loan Maturity

	Average Maturity					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post EP4 x non-Brown	-14.92	-2.236	-2.796	12.94	-4.279	28.88
	(13.46)	(13.18)	(13.19)	(14.90)	(16.63)	(30.35)
Fixed-effects						
Lender		Yes	Yes	Yes	Yes	Yes
Year x Quarter			Yes			
Year x Quarter x Country				Yes		
Year x Quarter x Industry					Yes	
Year x Quarter x Country x Industry x Size						Yes
Observations	4,395	4,395	4,395	4,395	4,352	4,352
R^2	0.08	0.48	0.49	0.74	0.61	0.93

*IID standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 7: Subsample Lender-Level and Loan-Level Analyses

This table shows the results from lender-level and loan-level difference-in-differences (DiD) analyses around the introduction of EP4 for subsamples where EP4 could be more impactful. Panel A presents the results from a DiD analysis on the greenness of EP lenders for the subsample of lenders outside of the EU. The analyses follow Equation (1) and the output is structured as the main lender-level output in Table 3. Panel B presents the results from a DiD analysis on the greenness of loans for the subsample of loans to projects in non-designated countries. The analyses follow Equation (2) and the output is structured as the main loan-level output in Panel B of Table 5.

Panel A: Lender-Level DiD: Lenders Outside the European Union

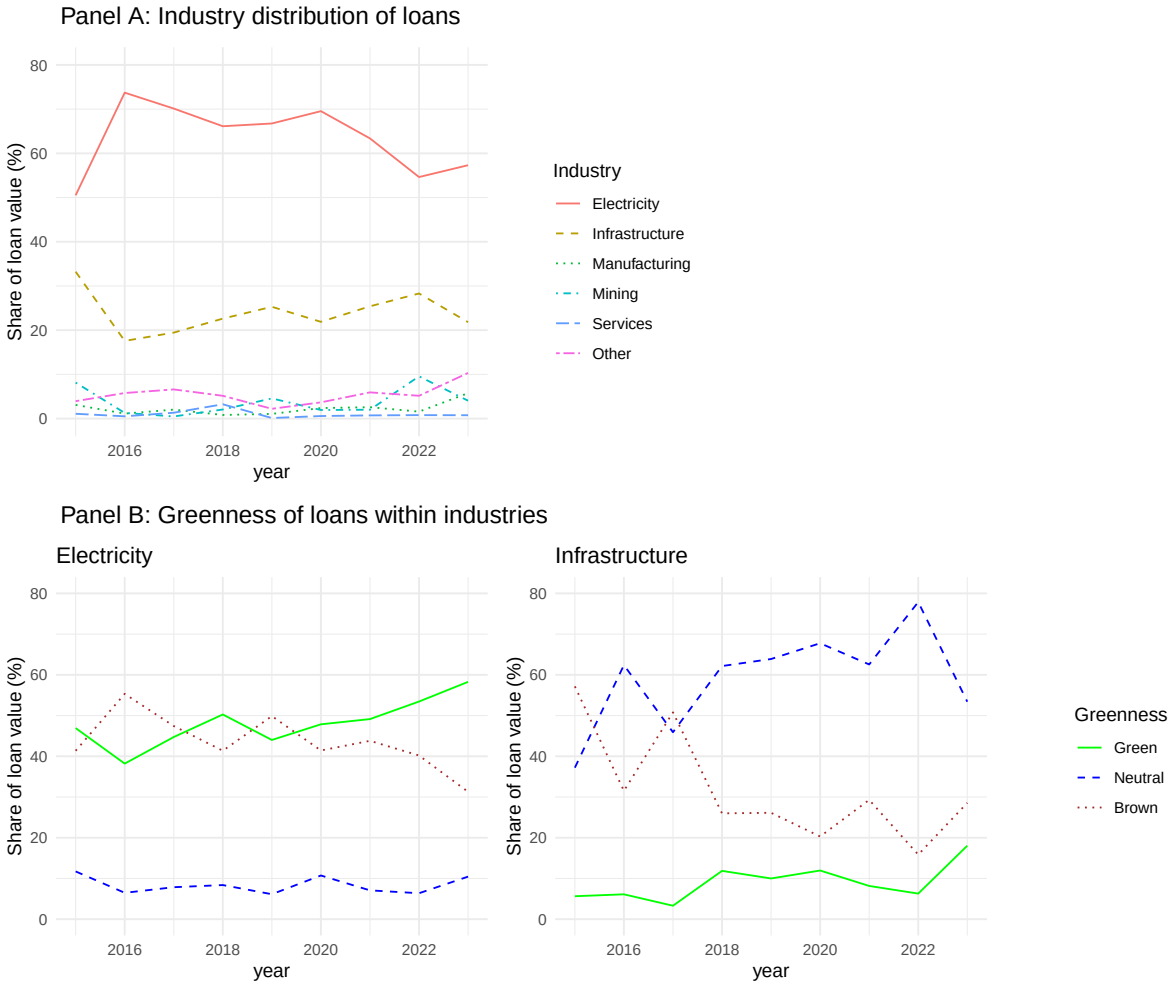
	Green Ratios		Neutral Ratios		Brown Ratios	
	Deals	Value	Deals	Value	Deals	Value
	Deals	Value				
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post EP4	-0.0281	-0.0711	0.0203	0.0313	0.0078	0.0398
	(0.0339)	(0.0384)	(0.0211)	(0.0396)	(0.0248)	(0.0321)
Fixed-effects						
Lender	Yes	Yes	Yes	Yes	Yes	Yes
Lender Country x Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,894	2,894	2,894	2,894	2,894	2,894
R^2	0.75	0.72	0.69	0.66	0.74	0.72

Panel B: Loan-Level DiD: Loans to Projects in Non-Designated Countries

	Non-Brown dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post EP4	0.1051**	0.0667	0.0766*	0.1169*	0.0391	-0.1033
	(0.0415)	(0.0439)	(0.0447)	(0.0699)	(0.0464)	(0.1009)
Fixed-effects						
Lender		Yes	Yes	Yes	Yes	Yes
Year x Quarter			Yes			
Year x Quarter x Country				Yes		
Year x Quarter x Industry					Yes	
Year x Quarter x Country x Industry x Size						Yes
Observations	2,316	2,316	2,316	2,316	2,293	2,293
R^2	0.01	0.45	0.46	0.75	0.71	0.97

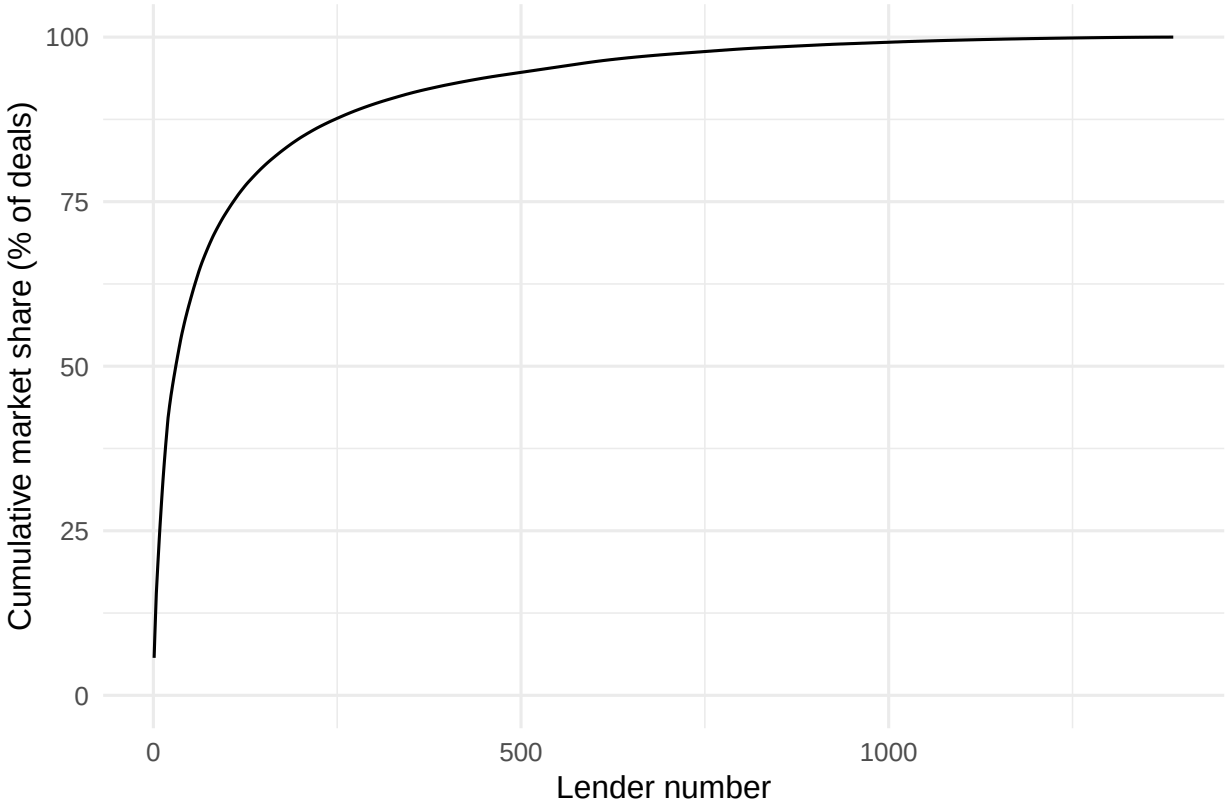
*Standard-errors in parentheses. Panel A: Clustered (Lender and Time). Panel B: IID. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Figure 1: Share of Project Finance Value by Industry and Greenness



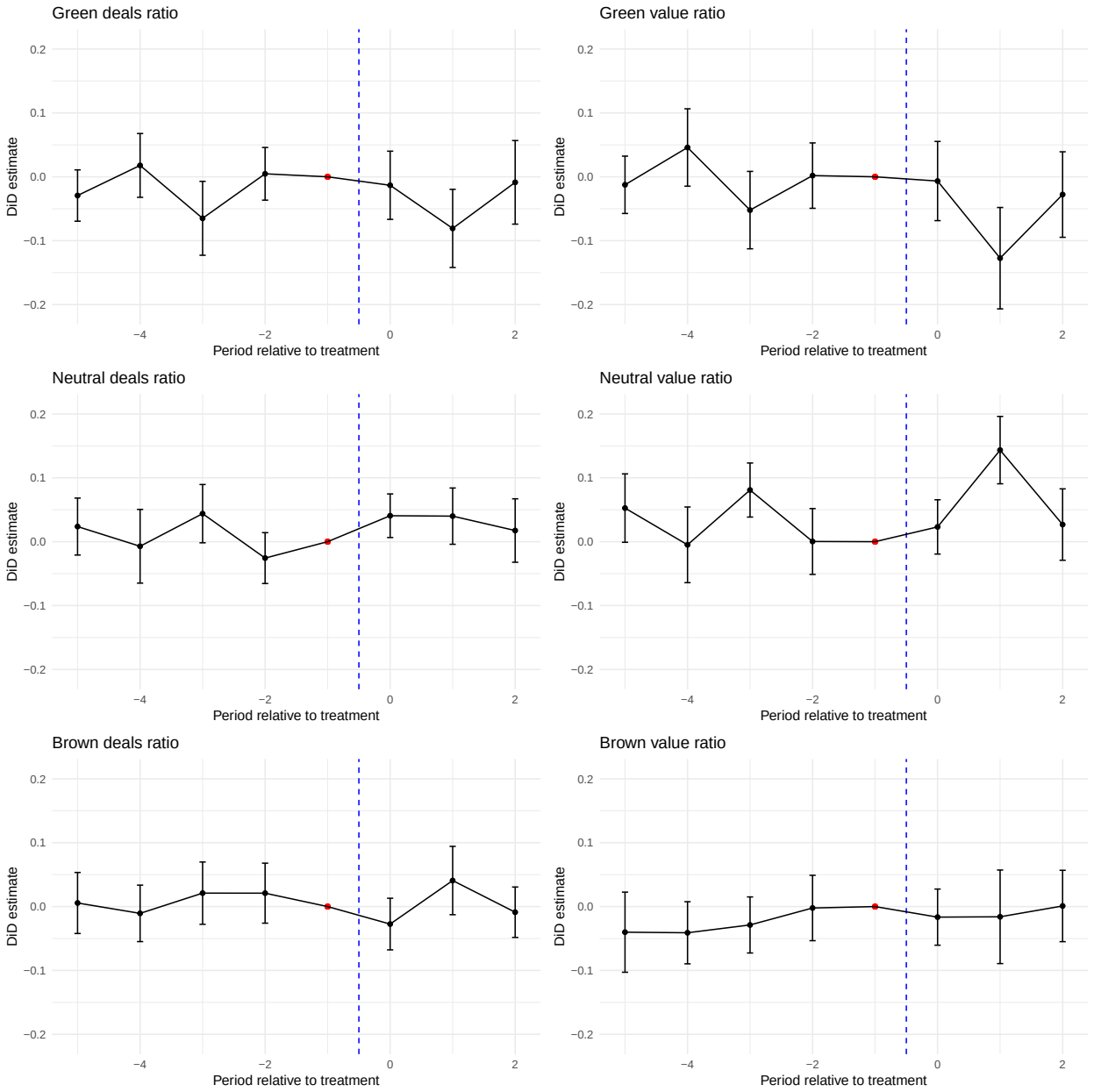
Panel A shows the share of value in project finance industries over time. Industries are based on project sectors reported by DealScan ('project_finance') manually grouped into broader categories. Electricity includes fuels and pipelines, and infrastructure includes construction and buildings. Panel B documents the greenness of the loans within these two key industries.

Figure 2: Lender Size Distribution



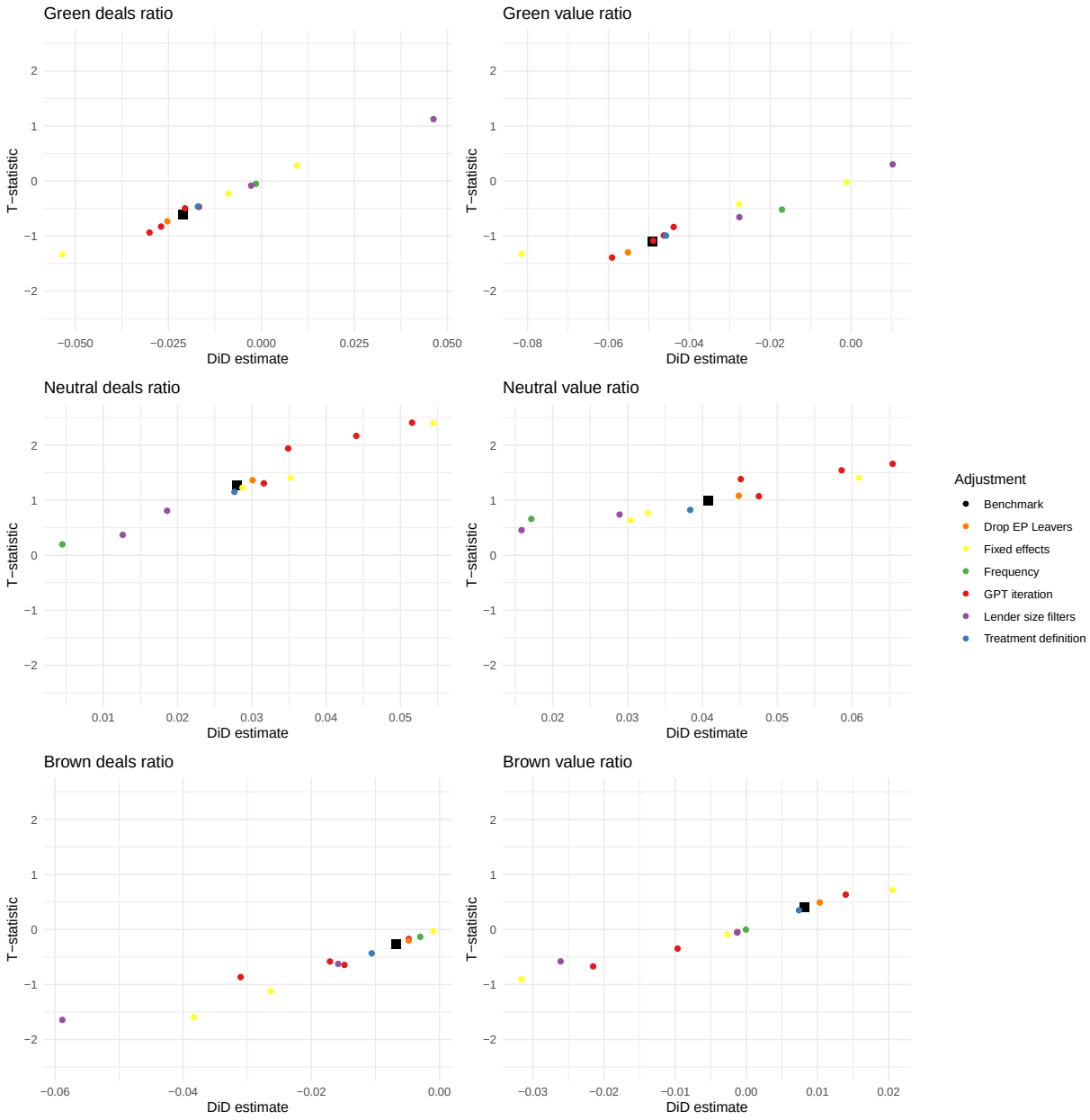
This figure shows the cumulative market share of the largest X lenders based on all project finance deals in our sample from 2015Q4 until 2023Q3.

Figure 3: Parallel Trends for Lender-Level Greenness



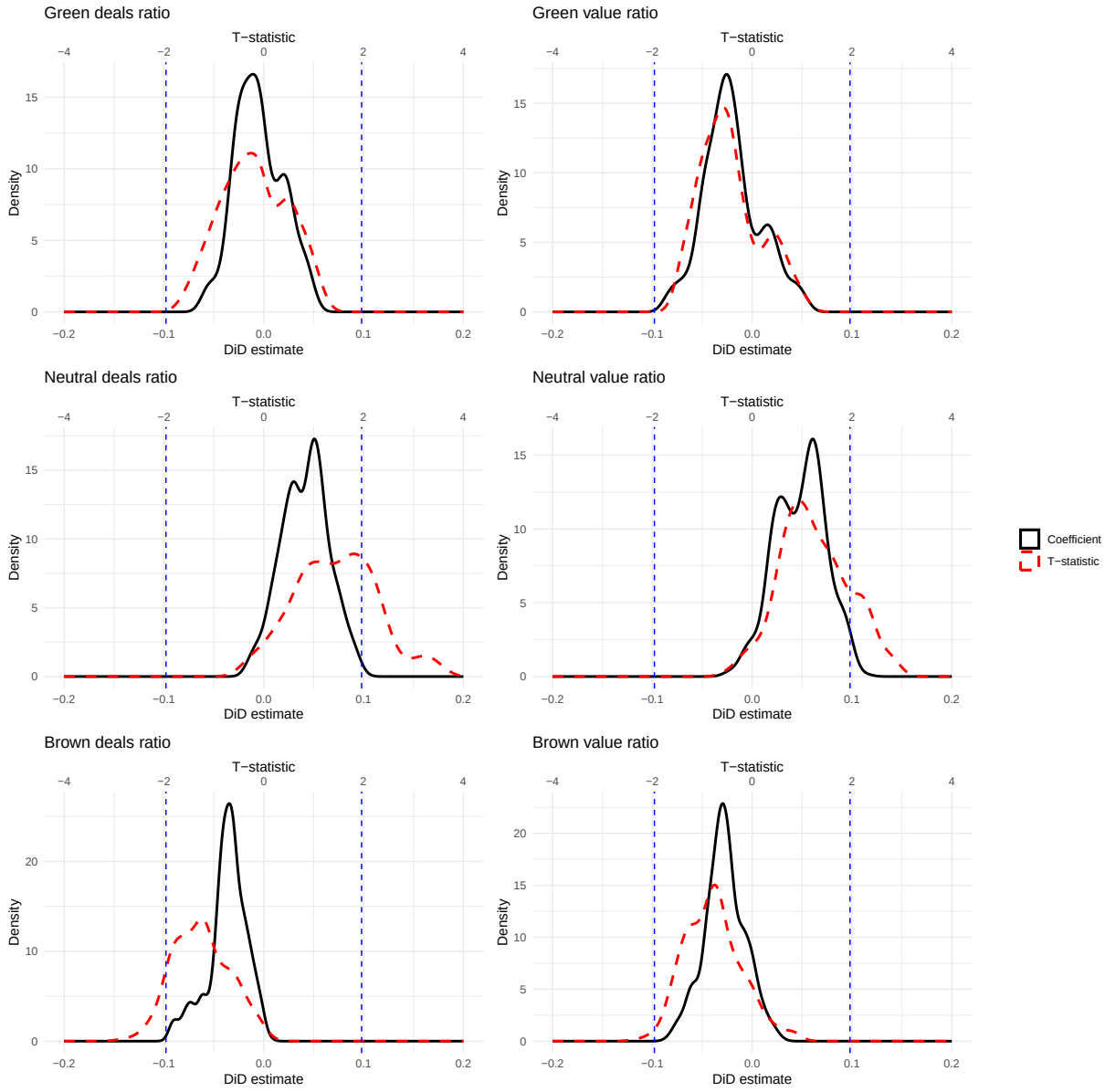
This figure presents the coefficients and 95% confidence interval from a dynamic DiD model corresponding to the lender-level DiD shown in Table 3. We regress the lender-level ratios of green, brown or neutral to total deals or values, respectively on a set of Treat × Period dummies and include fixed effects for Lender and Lender Country × Time. Standard errors are two-way clustered at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Period is 0 in the year starting in 2020Q4. The blue dashed line indicates the treatment timing. The red dot is the omitted period from the dynamic DiD. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.

Figure 4: Scatter of Coefficients and T-Statistics of Difference-in-Differences on Lender-Level Greenness Ratios



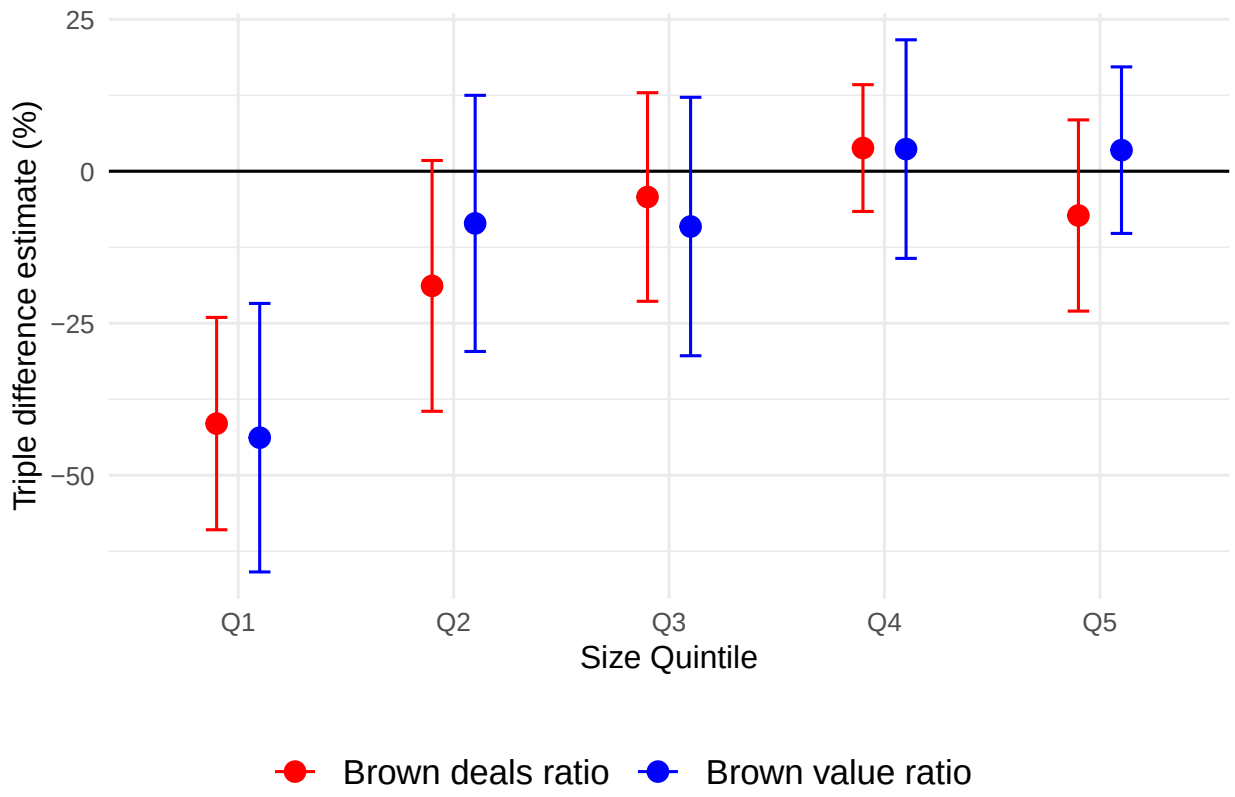
This figure shows the spread of coefficients and t-statistics for single deviations from the benchmark lender-level DiD models from in Table 3, keeping all other model specifications the same. We regress the green, neutral or brown deals or value ratio on Treat × Post EP4. Standard errors are two-way clustered at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. The coefficient from the benchmark model that includes fixed effects for Lender and Lender Country × Time is displayed as a black square. The dots are deviations from this model, all versions used within this figure are described in detail in Section 4.3. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.

Figure 5: Density of Coefficients and T-Statistics of Difference-in-Differences on Lender-Level Greenness Ratios



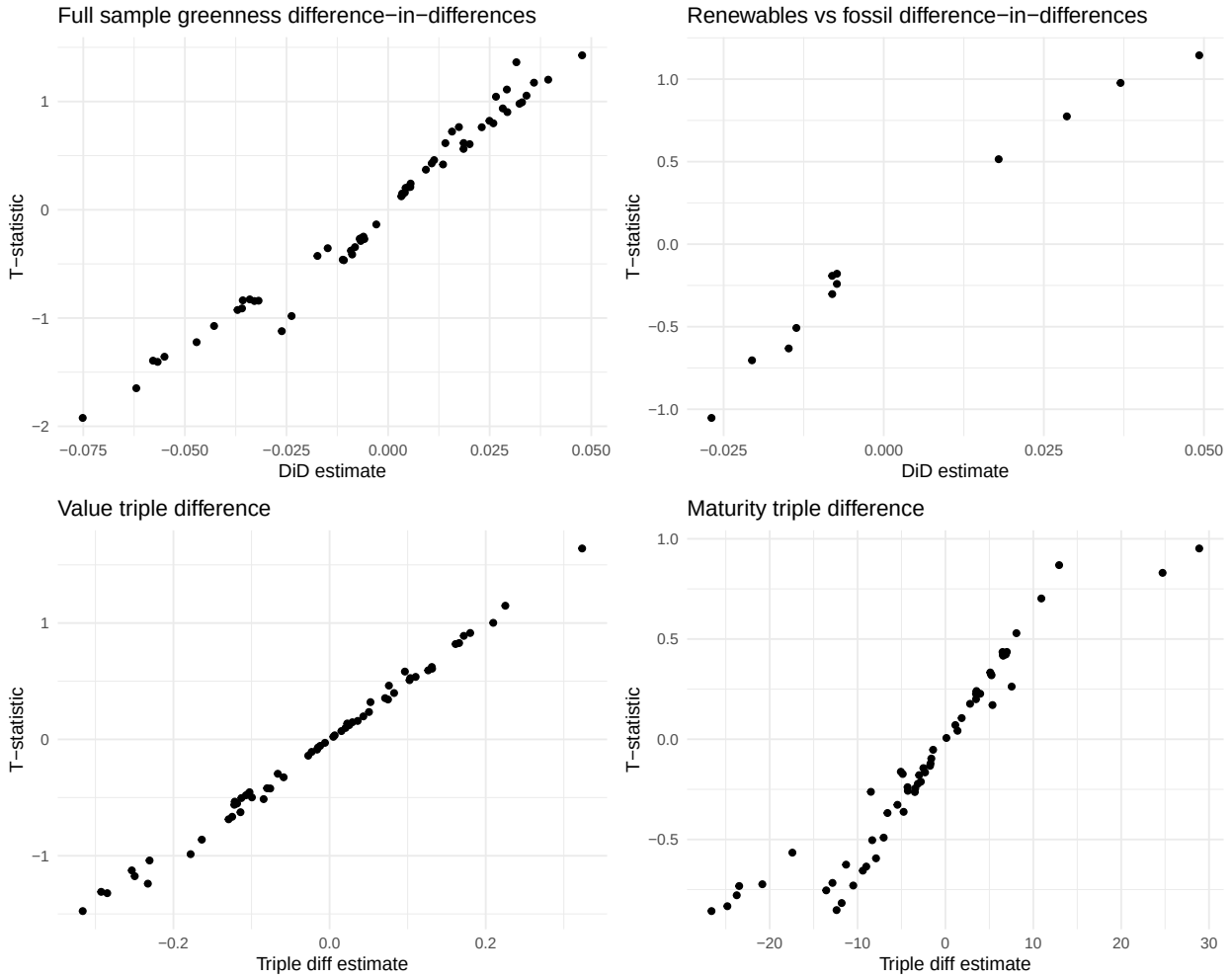
This figure shows the densities of coefficients and t-statistics for variations of the lender-level DiD models in Table 3. This figure includes all possible combinations of sample and model specifications described in Section 4.3, a total of 2880 variations from the benchmark model for each subplot. For each variation, we regress the green, neutral or brown deals or value ratio on Treat $\times$ Post EP4 and cluster standard errors two-way at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4. Each subplot contains two densities, one for the coefficient (bottom x-axis) and one for the t-statistic (top x-axis). The dashed blue lines correspond to t-statistics of -1.96 or +1.96.

Figure 6: Lender-Level Brown Ratios: Triple-Differences with Size Quintiles



This figure shows the results from splitting the baseline difference-in-differences analysis by lender size quintiles, by including a triple-difference term $Treat \times Post\ EP4 \times Size\ Dummy$ to Specification (1), and using unweighted regression. The figure presents the triple-difference coefficients and 95% confidence intervals for each size quintile (Q1 includes the smallest lenders, Q5 the largest). We only include lenders involved with at least ten deals in the four years pre-sample. The outcome variable is the ratio of brown deals or deal value to total deals or deal value in a Lender × Year. We include fixed effects for Lender and Lender Country × Time and controls for all single and two-way combinations of $Treat$, $Post\ EP4$, and $Size\ Dummy$. Standard errors are two-way clustered at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. The size dummy is 1 if the lender is part of a size quintile based on the number of deals in that Lender × Year, and 0 otherwise. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.

Figure 7: Scatter of Coefficients and T-Statistics of Loan-Level Difference-in-Differences and Triple-Differences



This figure shows the coefficients and t-statistics of alternative specifications for the project level DiD and triple-diff analyses from Tables 5 and 6. Variations from the benchmark settings are described in Section 5.3. The top panels present variations of the DiD analysis about the share of non-brown (top-left) and renewable energy (top-right) loans after EP4. We regress the loan level non-brown or renewables dummy on the treatment by EP4, respectively. The bottom panels present variations of the triple-diff analyses on the non-brown loan size and maturity after EP4 in the bottom-left and -right, respectively. We regress the loan size (log(value in mln USD)) or maturity (in months) on Treat $\times$ Post EP4 $\times$ non-brown. Post EP4 is 1 from 2020Q4, 0 before. The non-brown dummy is 1 for green and neutral deals, 0 for brown deals. Treat is defined in three ways, as described in Section 5.3. The sample uses quarterly loan level data and starts in 2015Q4 and ends in 2023Q3.

A Appendix

A.1 Individual Bank Analyses: Sample Selection and Data Collection

The results in Table 1 are based on lender-specific analyses. The sample includes the 25 lenders with the largest syndicated loan origination in 2022. To select these, we use all syndicated loan origination data in DealScan, as opposed to only selecting PF loans. The data cleaning otherwise follows exactly the same procedure as described for the PF loan sample in Section 3.1. Based on this, the 25 largest lenders in 2022 are Bank of America, Citi, Mitsubishi UFJ Financial Group, JP Morgan, Mizuho Financial Group, Sumitomo Mitsui Financial Group, Wells Fargo, BNP Paribas, Goldman Sachs, HSBC, Bank of China, Barclays, Credit Agricole, RBC Capital Markets, Deutsche Bank, PNC Bank, US Bancorp, ING Group, Societe Generale, Toronto Dominion Bank, Morgan Stanley, Banco Santander, Truist Financial, Scotiabank, and Credit Suisse. Together, these banks cover 56% of the global syndicated loan origination and 38% of the global PF syndicated loan origination in 2022.

In Table 1, we document how often these banks mention sustainability initiatives in their reports. We manually collect the annual reports for these banks for the years 2019 to 2022, as well as their 2022 ESG report. When the report does not cover an exact calendar year, we use the one closest to the year we analyze (e.g., when banks report from Q2 until Q1 next year, we take the April 2019 until March 2020 report as 2019 report). Annual reports are reasonably standardized but ESG reports are not. We take the most general ESG report available for each lender. For example, when the lender has a 'sustainability report', a 'climate report', and an 'Equator Principles report', we choose the 'sustainability report'. We fund such a report for 19 of the 25 lenders and use the 2022 annual report when the ESG report is not available. The motivation for this is that most lenders that do not have an ESG report explicitly refer to the annual report for ESG information.

Within these reports, we count the number of times a green initiative is mentioned. We run a simple text search for 'Initiative name', 'Abbreviation' and 'Initiative name (Abbreviation)' and define the number of times an initiative is mentioned as the exact matches for the first two, minus the matches for the last search. This method avoids double counting when abbreviations are introduced. We then report the total mentions for each initiative by all banks for each report type times year in Table 1, as well as the percentage of banks that mention these initiatives.

We also collect membership in other initiatives. We manually collect these data. We count a bank as 2022 member of the NZBA, PRB, and SBTi when we find them on the respective websites of these initiatives with a commitment date before the end of 2022. We count banks as member of the CDP when the status of the 'Climate Change 2022' questionnaire by CDP is 'Submitted', indicating that they voluntarily disclosed information. The TCFD has both active members (who shape the initiative) and supporters (which is a large set of firms). We

follow Hasan et al. (2023) to only count TCFD members.[22]

Since NZBA and PRB also report historical membership changes (banks that unlisted), we can track the membership to these initiatives well. For SBTi, we only observe banks that are currently found in the SBTi dashboard (accessed in November 2024). Therefore, we may underestimate the 2022 SBTi membership if the 25 banks we analyze pledged before or in 2022 but unlisted afterwards. We manually search for SBTi information for each bank in our sample and find that HSBC and Societe Generale left the SBTi after 2022 - we include these as 2022 members. In addition, a case study about Mizuho's implementation of the SBTi is available online, which we take as an indication that they were also a likely member.[23] Any missed previously-signed members potentially explain that the SBTi is mentioned by more banks than we confirm membership of, as reported in Table 1.

A.2 Measuring the Greenness of Loans: ChatGPT Prompt

This appendix provides more details on the classification of projects using GPT. We accessed GPT using OpenAI's API. We ran the evaluation on February 4, 2024, using the model *gpt-4*, which at this time pointed to *gpt-4-0613*. We set the temperature parameter to 0 and instruct the model to use a fixed seed. We pass along the following system role, which instructs GPT about its "personality":

> You are a research assistant specialized in classifying the environmental impact of projects. You are diligent and always report data in the requested format.

As prompt (user role) we pass the text below followed by a comma-separated list of 50 deals with the information referenced in the text (and no other columns).

> Below you can find a comma-separated CSV file. The CSV file contains data about 50 projects financed by banks. Each row represents one project. The data has the following variables in the columns:
>
> - deal_no: unique deal identifier
> - unique_broad_industry_group: industry classification of the borrower
> - unique_major_industry_group: industry classification of the borrower's activities
> - unique_sic_code: SIC industry classification of the borrower
> - unique_naic: NAICS industry classification of the borrower

[22]The websites used are https://www.unepfi.org/net-zero-banking/members/ for NZBA, https://www.unepfi.org/banking/bankingprinciples/ for PRB, https://sciencebasedtargets.org/companies-taking-action for SBTi, https://www.cdp.net/en/responses for CDP, and https://www.fsb.org/2016/05/fsb-names-additional-members-of-the-task-force-on-climate-related-financial-disclosures/ for TCFD.

[23]The case study is available here https://sciencebasedtargets.org/resources/files/Financial-Sector-Science-Based-Targets-Guidance.pdf.

- unique_parent: firm name of the borrower
- unique_project_finance: classification of the project
- unique_purpose_remark: unstructured description of the project
- unique_deal_remark: unstructured description of the project

Use this information to do the following:

1. Classify each of the projects according to their environmental impact as "green", "brown", or "neutral".
2. Provide a brief motivation for the classification. Keep the motivation short by not always writing out full sentences and omitting uninformative words.
3. Provide a score for how certain you are about the classification of the project's environmental impact, with 100 = very certain and 0 = uncertain.

Provide the output as a new CSV file with four columns. There should be no header row, and the columns should have the following content:

- deal_no identifier from the original file
- Classification (item 1 from the list above)
- Motivation (item 2 from the list above)
- Certainty Impact Evaluation (item 3 from the list above)

Your response should only contain the CSV file and no other text. In the CSV file, make sure to use quotation marks, so that commas are only used as separators. Remember not to include a top row with column names, and output exactly as many rows as there are deals!

Table 8: Comparison of Five Rounds of Greenness Classifications

This table compares the greenness classifications of five rounds of output from the GPT-4 model. Panel A documents the frequency of each category in these five rounds. Panels B to D show the correlations between the green, neutral, and brown classifications in each round, respectively. For this, we create a dummy that equals 1 when the classification is green, neutral, or brown, and 0 otherwise. These panels show the correlations between these dummies.

Panel A: Frequency of Categorization

	Round 1	Round 2	Round 3	Round 4	Round 5
Green	3494	3494	3499	3462	3477
Neutral	1268	1197	1255	1293	1279
Brown	1267	1248	1275	1253	1275
Missing	59	149	59	80	57

Panel B: Correlation of Green Dummies

	Round 1	Round 2	Round 3	Round 4	Round 5
Round 1	1	0.9	0.93	0.94	0.93
Round 2	0.9	1	0.93	0.91	0.92
Round 3	0.93	0.93	1	0.93	0.93
Round 4	0.94	0.91	0.93	1	0.95
Round 5	0.93	0.92	0.93	0.95	1

Panel C: Correlation of Neutral Dummies

	Round 1	Round 2	Round 3	Round 4	Round 5
Round 1	1	0.81	0.83	0.84	0.84
Round 2	0.81	1	0.81	0.83	0.81
Round 3	0.83	0.81	1	0.84	0.83
Round 4	0.84	0.83	0.84	1	0.87
Round 5	0.84	0.81	0.83	0.87	1

Panel D: Correlation of Brown Dummies

	Round 1	Round 2	Round 3	Round 4	Round 5
Round 1	1	0.88	0.92	0.9	0.91
Round 2	0.88	1	0.9	0.9	0.91
Round 3	0.92	0.9	1	0.91	0.9
Round 4	0.9	0.9	0.91	1	0.92
Round 5	0.91	0.91	0.9	0.92	1

A.3 Additional Output

Table 9: Variable Definitions and Data Sources

Lender x year variables	**Definition**	**Source**
Treat	Lender is EP member before 2020Q4.	Equator Principles Association
Post EP4	Dummy; 1 from 2020Q4.	
Renewable deals/value ratio	Sum of renewable deals or deal value to the total of renewable and fossil energy deals or deal value.	DealScan + Manual classification
Green/neutral/brown ratios	Sum of green/neutral/brown deals or deal value to the total deals or deal value.	DealScan + GPT-4 classification
Loan variables	**Definition**	**Source**
Treat	Dummy; 1 if loan is larger than 10mn USD (deal_amount_converted) and from 2020Q4.	DealScan
Post EP4	Dummy; 1 from 2020Q4	
Treat intensity	[0-1]; 0 if loan is smaller than 10mn USD. Otherwise, number of EP lenders divided by total number of lenders.	DealScan + EPA
Treat lead intensity	[0-1]; 0 if loan is smaller than 10mn USD. Otherwise, number of EP lead lenders divided by total number of lead lenders.	DealScan + EPA
Renewable dummy	Dummy within the subset of renewable and fossil fuel energy deals; 1 if renewable, 0 otherwise.	DealScan + Manual classification
Non-brown dummy	Dummy; 1 if green or neutral, 0 if brown.	DealScan + GPT-4 classification
log(value)	Natural logarith of the project loan value in USD mn (log(deal_amount_converted)).	DealScan
Maturity	Value weighted sum of maturities (in months) of each tranche in a project.	DealScan
Lead lender	Lender roles (primary_role or additional_roles) include "Agent", "Arranger", "Lead", or "Manager".	DealScan
Lender	lender_parent_id.	DealScan
Industry	SIC 2-digit.	DealScan
Size	Quintiles sorted within each time period based on deal_amount_converted.	DealScan

Table 10: Difference-in-Differences for Lender- and Loan-Level Greenness: No Neutral Loans

This table shows the results from difference-in-differences analyses on the greenness of EP lenders (Panel A) and loans (Panel B) after the introduction of EP4. These results follow the same structure of Table 3 for the Lender-Level analysis (Panel A) and Table 5 for the Loan-Level analysis (Panel B). The sole difference in these regressions is that we drop all loans classified as neutral from the sample. I.e., there are only green and brown loans in these tables. The rest of the variable definitions, methods, and sample construction follows Table 3 and Table 5 exactly.

Panel A: Lender-Level Greeness Ratios without Neutral Loans

	Green Ratios		Brown Ratios	
	Deals	Value	Deals	Value
	(1)	(2)	(3)	(4)
Treat × Post EP4	0.0046	-0.0272	-0.0046	0.0272
	(0.0306)	(0.0323)	(0.0306)	(0.0323)
Fixed-effects				
Lender	Yes	Yes	Yes	Yes
Lender Country x Time	Yes	Yes	Yes	Yes
Observations	3,212	3,212	3,212	3,212
R^2	0.78	0.75	0.78	0.75

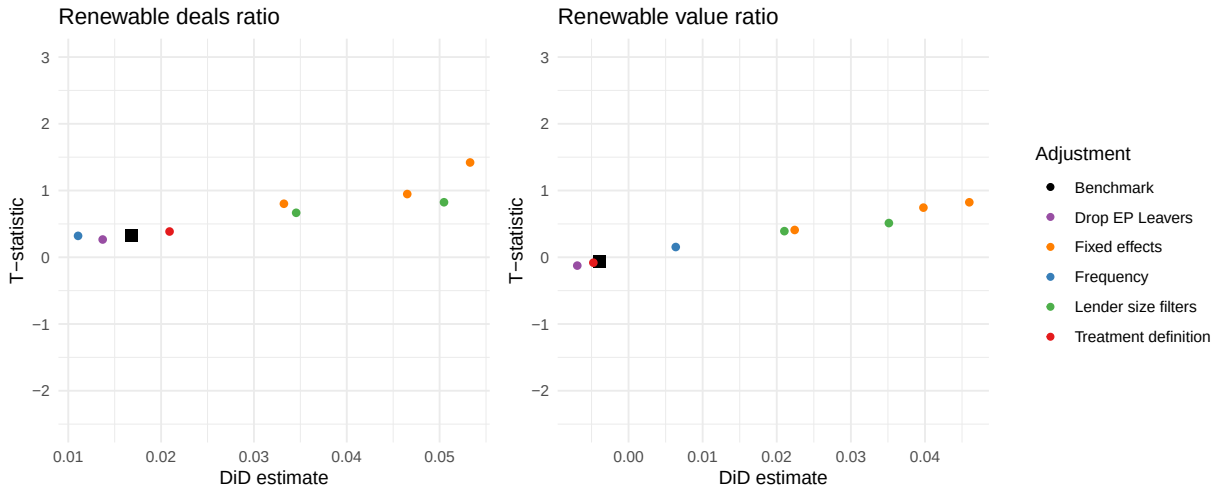
Panel B: Loan-Level Greenness without Neutral Loans

	Non-Brown dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post EP4	0.0306	0.0182	0.0176	0.0536	-0.0062	-0.0452
	(0.0274)	(0.0271)	(0.0272)	(0.0362)	(0.0222)	(0.0426)
Fixed-effects						
Lender		Yes	Yes	Yes	Yes	Yes
Year x Quarter			Yes			
Year x Quarter x Country				Yes		
Year x Quarter x Industry					Yes	
Year x Quarter x Country x Industry x Size						Yes
Observations	4,761	4,761	4,761	4,761	4,718	4,718
R^2	0.00	0.42	0.43	0.67	0.73	0.94

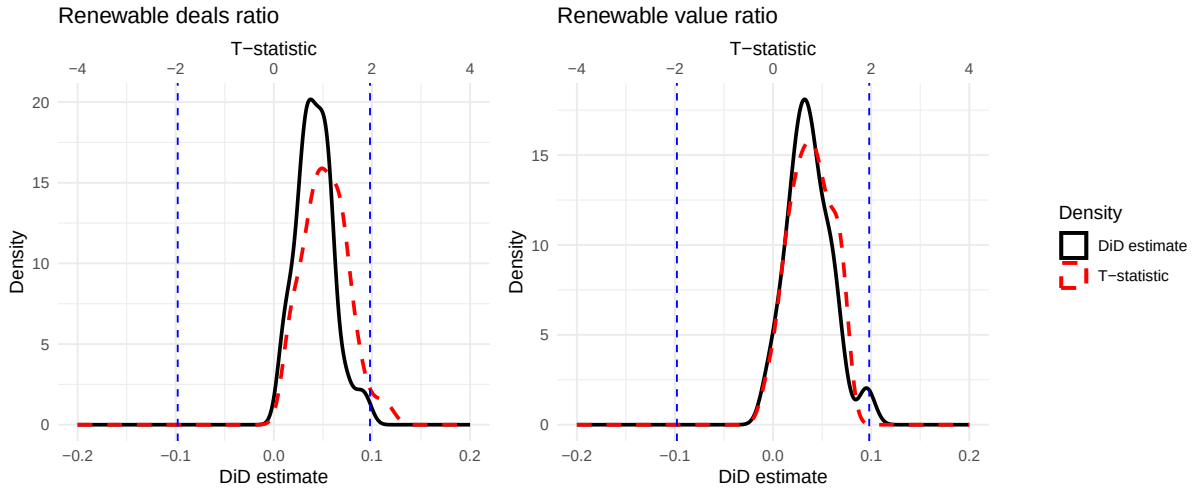
*Standard-errors in parentheses, clustered (Lender and Time) in Panel A, IID in Panel B. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Figure 8: Distribution of Coefficients and T-Statistics of Difference-in-Differences on Lender-Level Renewables Ratios

Panel A: Scatter of Coefficients and T-Statistics



Panel B: Density of Coefficients and T-Statistics



This figure shows the coefficients and t-statistics for variations of the lender-level DiD models in columns (1)–(2) of Table 3. The analysis focuses on the sub-sample of renewable and fossil energy projects. We regress the ratio of renewable deals or deal value to the joint number or deals or deal value in renewable and fossil energy projects on Treat × Post EP4. Standard errors are two-way clustered at the Lender and Time dimensions. Treat is set to 1 when the lender is an EP member before EP4 becomes effective, 0 otherwise. Post EP4 is 1 from 2020Q4, 0 before. In Panel A, we plot single deviations from the benchmark model that includes fixed effects for Lender and Lender Country × Time. The benchmark from Table 3 is displayed as a black square. In Panel B, we include all possible combinations of sample and model specifications described in Section 4.3. The sample starts in 2015Q4 and ends in 2023Q3. Data is annualized from quarterly data in year t Q4 until year $t+1$ Q3 to match the treatment that occurs in Q4.