Do Voluntary Pledges Make Loans Greener?

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Abstract

We analyze whether voluntary green pledges by lenders result in greener loan origination in the project finance (PF) market. This market is of key importance for financing climate-relevant projects globally. We can classify the environmental impact of expenditures financed through PF loans because projects are single-purpose developments. We exploit a tightening of the Equator Principles (EP) that introduced comprehensive climate risk management requirements to PF loans. This allows us to disentangle the effect of a lender's sign-up decision from the impact of the pledge itself. We find no evidence for a shift to greener lending by EP members after the tightening. We corroborate this null result using a wide range of alternative model specifications.

JEL classifications: G21

Keywords: Project Finance, Green Lending, Climate Risk, Equator Principles

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1 Introduction

Many lenders make green pledges by joining initiatives that commit its members to account for climate change in their lending activities. These pledges range from commitments to implement climate-related financial disclosure, to practice climate risk management, or to support the transition to a net-zero economy. An important question is whether such green pledges result in greener loan origination.

We answer this question in a setting that (i.) allows for a clear measurement of a loan's environmental impact, (ii.) is of key importance for the green transition, and (iii.) enables us to disentangle the effect of the green pledge from the effect of a lender's sign-up decision. Our setting is the global market for project finance (PF), in which the Equator Principles (EP) is the key green pledge focused on Environmental and Social (ES) risk management. PF allows us to cleanly analyze the environmental impact of expenditures funded by new loans, because PF loans support single-purpose developments such as wind farms and coal mines. PF is of key importance for the green transition because it accounts for a large share of new developments in renewable energy and fossil fuel energy globally. We disentangle the effect of the green pledge from the effect of a lender's sign-up decision by exploring a change to the EP that affects previously committed lenders.

PF loans fund single-purpose developments, and we employ two different approaches to classifying their environmental impact. The first approach limits the sample to energy projects. Within this sub-sample, we classify projects as renewable or fossil fuel energy based on a simple keyword matching procedure. Using this approach, we are able to classify 57% of all the projects in the full sample. This classification is very precise; we manually confirm that the measurement error is small. Second, we use OpenAI's GPT-4 model to classify projects into green, neutral, or brown, based on industry codes and unstructured text in the loan purpose description. This allows us to make use of the full sample and to better exploit the information contained in the unstructured textual project descriptions. For a subset of deals, we verify manually that this allows us to measure the environmental impact of projects remarkably well. These two approaches enable us to directly classify the expenditures funded by a loan. In contrast, the greenness of firm-level lending is often analyzed based on borrowers' greenness (for example, see Kacperczyk and Peydró, 2021), regardless of whether the funding supports green or brown expenditures.[1]

PF is a market of key importance for the green transition. PF loans support new developments that are often financed off-balance sheet in a special purpose vehicle (SPV). Supported projects usually involve energy infrastructure or large-scale constructions such as highways: over 2015–2023, 60% of projects were in energy and another 25% in infrastructure. In 2022, the PF loan market financed $363.1 bn in 953 large-scale projects globally (Refinitiv, 2022). According to FS-UNEP (2016), 52% of new renewable energy projects globally were financed through PF instead of corporate loans in 2015. The PF market is also relevant for financing brown, fossil-fuel based energy projects. Combining data from Global Energy Monitor (2023) and Global Energy Monitor (2024) on newly developed coal plants outside of China, we estimate that 60% of new coal capacity between 2010 and 2023 is financed through PF.[2]

Examining the impact of green pledges is challenging because a lender's decision to join a green initiative is endogenous. In our analysis we focus on a tightening of green pledges applicable to existing members of the initiative, by analyzing the implementation of a new version of the EP (EP4) in October 2020. The key change in EP4 is that EP members (EP Financial Insitutions, EPFIs) need to implement climate risk assessments to new PF loans with high emissions or other environmental externalities. Effectively, it amounts to a significant new requirement for sourcing brown loans and also additional external scrutiny when making such loans as EP members have to publish the risk assessment. The focus on the move to EP4 allows us to disentangle the tightening of the green pledge on existing signatories from factors that led to their sign-up decision. To the best of our knowledge, we are the first to analyze the causal impact of a tightening in green pledges on the credit allocation of their members.

We first test whether EPFIs become greener after this shock. Specifically, we run a lender-

[1] The distinction is particularly relevant since significant "greening" activities take place in firms that would be classified as brown based on their ESG-score or carbon emissions. For instance, firms with low ESG scores are key green patent innovators (Cohen et al., 2021) and PE investment in fossil fuels causes a switch to greener technologies locally (Kumar, 2023).

[2] Data from Global Energy Monitor (2023) does not include China. As a lower-bound global estimate, if we assume that no coal power plants in China were funded through PF, PF still supports 22.2% of global new capacity. We focus on coal in this example because it is the highest emitting energy source. Global Carbon Budget (2023) documents that coal is responsible for 41% of global carbon dioxide emissions in 2022.

level difference-in-differences (DiD) model around the implementation of EP4, where the outcome variable is the (value-weighted) lender-level ratio of renewable to total renewable and fossil fuel PF deals. We also analyze green, neutral, or brown to total deals, where we include all projects, also those unrelated to renewable and fossil fuel energy. For both the number of deals and deal values, we find that EPFIs do not shift from fossil to renewable energy deals, nor from brown to green or neutral deals, compared to other lenders. This indicates that the implementation of climate risk assessments does not affect the greenness of credit allocation.

We analyze the impact of our modelling choices by running thousands of specifications for our key regressions. Among other things, we analyze projects in different geographies, include different fixed effects, and define treated lenders and loans in alternative ways. We then collect the coefficient of interest and the corresponding t-statistics from these specifications. These are roughly centered around zero. Overall, irrespective of modelling choices, we cannot detect a consistently significant effect of EP4 on green, brown, or neutral lending.

Next, we examine the greenness of loan outcomes in a set of loan-level regressions, which allow us to control for demand effects using time-by-country-by-industry-by-size fixed effects, following an approach similar to Degryse et al. (2019). In a DiD model, we show that neither the share of renewable loans, nor the share of non-brown PF loans increases when EP4 is applied. In further triple-difference analyses, we observe that non-brown PF loans also do not change in size or maturity. Thus, neither at the lender level nor at the loan level do we observe a shift to greener outcomes. We again confirm that this null-result is robust to a wide range of modeling choices.

While we document that green pledges by lenders do not cause greener credit allocation, this by no means implies that these initiatives are ineffective. For example, EP4 may lead lenders to better understand the environmental risks originating from brown lending. It may also allow them to select brown deals with lower environmental risks, further improving risk management and control.

Our findings have immediate policy relevance. We show that voluntary green pledges and climate risk management do not have to result in greener loan origination. If policymakers wish to incentivize green lending, they may have to take a step beyond voluntary commitments by lenders. Regulation such as higher capital requirements for brown loans may be required.

1.1 Related Literature

We contribute to the literature on green pledges. A number of papers document that banks adjust their lending after signing up to a green initiative, while the evidence on firms' environmental performance is more mixed. 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 no improvement in firms' environmental performance. 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, but find affected firms improve their environmental performance. Green and Vallee (2024) document that bank exit policies negatively affect the financing and operation of coal assets, resulting in a reduction in carbon emission. By contrast, Sastry et al. (2023) find no effect on lending outcomes for European banks signing up to Net Zero Banking Alliance. Our contribution to this literature is that we analyze the project finance market, which is an underexplored market that is important for the green transition and allows to directly classify the environmental impact of the expenditures financed by a loan. In addition, we are the first to disentangle the within-pledge impact from the lenders' decision to make green pledges.

We also contribute to the literature that specifically studies the EP. Most of these studies focus on how EP members differ from non-members. Scholtens and Dam (2007) document that the earliest EP adopters were larger and had better corporate social responsibility policies than other banks. Eisenbach et al. (2014) show that EP members grow their PF market share after joining. Contreras et al. (2019) show that peer pressure and collaboration with current EP members predicts future EP membership. Sautner et al. (2022) document that EP members have green preferences: they offer lower interest rates in syndicated loan markets for firms with better EU taxonomy alignment, more so than the other lenders in the sample. We contribute the first analysis of causal impact of the EP on the greenness of credit allocation of its members.

More broadly, we contribute to the literature on green lending[3] by analyzing the impact of green pledges on the greenness of credit allocation.

2 Institutional Setting: Equator Principles

The EP is a risk management framework focused on ES risk in the PF market. While the initial focus is risk management, there is a secondary motive to have a positive impact. This is observed in the EP Association (EPA) strategy, which 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."[4] Our research dives into how these motives interact by quantifying the impact of climate risk management on the greenness of loan outcomes.

The EP framework is applied globally and across all industries to any new project that fits certain criteria. For example, it is applied to newly originated PF loans of projects with a capital cost of at least US$10 mln. The EP covers more than just PF loans. It applies to PF advisory services (PFAS), project-related acquisition finance and broader products in the PF market as well. We focus on PF-related syndicated loans, which does not include PFAS but includes the other components within the scope of the EP.

The EP started in 2003 and has grown to 138 lenders in December 2023. These lenders are large players in the PF market and are together involved with more than half of the recent PF syndicated loans. There have been several revisions to the EP framework. It started with a sole focus on PF loans, after which the scope increased to include PFAS with the introduction of EP2 in 2006. The introduction of EP3 in 2013 adds requirements for emissions estimations and reporting. The most recent update is the introduction of EP4 in October 2020, which tightens climate risk management practices. We explore the impact of the implementation of EP4 on the greenness of loan outcomes.

[3] Among others, Fatica et al. (2021); Giannetti et al. (2023); Ivanov et al. (2023); Kontz (2023); Luneva and Sarkisyan (2022); Walz (2022)

[4] These sentences are from Equator Principles Association (2022), page 9 and https://equator-principles.com/about-us/.

The most important change in EP4 is a new requirement to apply climate risk assessments to newly originated projects with high emissions or other environmental externalities.[5] We confirmed with practitioners who work in project finance and are involved in implementing the EP at a major EPFI, that these climate risk assessments are the most relevant and impactful change within EP4.[6] They also confirmed that the climate risk assessments are a significant effort that largely affect brown loans. Additionally, we note that EPFIs have incentives to implement climate risk assessments properly because their outcomes are partly disclosed. According to the EP4 guidelines, EPFI 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, there is a demanding increase in climate risk management standards that has heterogeneous impact on loans based on their greenness. Additionally, given its focus on climate risks, EP4 may have reinforced EP members' motive to have a positive impact through PF lending. Therefore, we hypothesize that EP4 results in a shift from brown to green project finance among EPFIs.

Importantly for our empirical identification, the implementation of EP4 is plausibly exogenous to the lender's sign-up decision. The EP started in 2003 and most lenders joined long before EP4, so that lenders could not anticipate EP4 at the time of joining.[7] Additionally, given that there are many members, no single lender has disproportionate influence on designing EP changes. Therefore, this setting offers a natural experiment that enables us to disentangle the effect of a lender's desire to signal its green credentials through the sing-up from the effect of the pledge itself. In particular, our setting based on variation within the EP enables us to study the causal impact of climate risk management on the greenness of loan outcomes.

[5] A more extensive summary of the development of the EP framework over the years is available on page 8 of Equator Principles Association (2023). Next to climate risk management, EP4 broadens the scope of the EP to include refinancing and acquisition finance, and it increases requirements within "designated countries", which the EP defines as countries that are both OECD member and on the World Bank High Income list.

[6] EP4 tightens the EP framework in a few other ways. Some of these changes are relatively minor. For example, 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. We verified that this is not something that occurs often. Thus, we argue that impact from the tightening of EP4 is mostly related to the application of climate risk management.

[7] A few lenders join the EP shortly before EP4. These lenders could be well-informed about anticipated changes to the EP framework. This concerns a small part of observations in our sample, and we confirm that removing these lenders does not affect our results.

While lenders still face an endogenous decision to remain EP members after EP4, the signalling incentives are plausibly much weaker compared to the sign-up decision. Consistent with this, we confirm that de-listings are uncommon in our sample (there are none before 2022) and occur due to reasons unrelated to the EP framework.[8] Given that the first de-listing occurs two years after the implementation of EP4, we argue that this is not a major concern for our identification. Additionally, in robustness tests we confirm that excluding lenders that de-listed within our sample period does not affect our results.

3 Data

3.1 Project Finance Syndicated Loans

We obtain all newly originated PF syndicated loans between the fourth quarter of 2015 and the third quarter of 2023 from DealScan.[9] 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 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 (in USD) are reported within a tranche or deal, where the tranche amounts do not sum to the deal amount, or where the deal amount equals zero. We require approximate matches to avoid throwing out deals because of rounding differences.

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

[8] 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 de-listed 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/). We have not seen any indications that EPFIs de-list because they do not want to apply the EP framework.

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

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[10] 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.

The final sample consists of 6,029 deals with involvement of 1387 unique lenders. The average deal has a volume of 304 mln USD and 3 participating lenders.

3.2 Measuring the Greenness of Loans

PF allows measuring the environmental impact of individual loans because loans support single-purpose developments. One challenge is that projects do not have an environmental rating or other direct measure of environmental impact. To classify projects, we use the project description in the deal and purpose remarks, together with industry identifiers and the name of the parent company provided in DealScan.[11] We use two different approaches to classifying projects. The first approach limits the sample to energy projects and classifies deals as fossil fuel or renewables energy projects based on a simple keyword search. Second, to exploit the full sample, we use OpenAI's large language model GPT-4 to perform the classification.

For our energy sub-sample analysis, we first select projects based on the energy industry identi-

[10] We consider roles in both the 'primary_role' and 'additional_roles' variables from DealScan.

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

fiers.[12] These are 4,351 out of the 6,029 projects in our sample. Within this sub-sample, we search for keywords from a list of words related to renewable or fossil fuel energy, respectively.[13] We then classify projects as renewable or fossil fuel if they *only* match words from the corresponding list, resulting in 3,376 classifications.[14] Of the 72 projects with keywords from both lists, we are able to manually classify 49. These are cases such as solar farms on former coal mine locations. For the remaining 23 projects, the project description is empty or uninformative. We leave these projects unclassified. We also leave projects without any keyword match unclassified. This results in a sub-sample of 3,425 energy projects that are classified as renewable or fossil fuel. This sub-sample covers 79% of the energy projects and 57% of all projects in our sample.

While a keyword search is sufficient to classify a large number of deals in the subset of renewable and fossil fuel energy projects, there are many projects that are harder to classify based on simple keyword matching. The reason is that the textual information in the project descriptions is unstructured, and simple keyword analyses are not sufficiently flexible in extracting information from unstructured text. To overcome this challenge, we use OpenAI's large language model GPT-4 to perform the classification. We design a prompt that instructs GPT to evaluate the environmental impact of a project based on the provided information, and classify the project as green, neutral, or brown. The exact prompt is provided in Appendix A.1. In addition to the classification, we ask GPT to provide the underlying motivation for the classification and a certainty score. Requesting a motivation forces the model to make a consistent argument for each classification, which provides context that can improve the classification precision. We remove deals where the model returns zero certainty and confirm that these are deals that are indeed hard or impossible to classify. For

[12]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.

[13]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.

[14]To confirm that these are indeed renewable or fossil energy projects, we manually check 50 each. 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 very small.

example, sometimes the only information is that the deal is used to refinance a previous loan.

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 context. To ensure the context is similar across batches, we randomize deals into batches.

We ensure that we prompt the GPT-4 model in the most replicable way by fixing a seed and turning creativity off (temperature equals zero). Nevertheless, some random variation in output from the model remains. Therefore, we run the entire evaluation five times and analyze how our results compare across these evaluations. Reassuringly, the classifications from different iterations overlap reasonably well. Table 5 Panel A 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. Overall, these steps result in a relatively clean measure of green versus brown lending.

We combine these loans at the lender level for our initial analysis, annualizing observations from the fourth quarter of year t until the third quarter of year $t + 1$ to match the treatment timing in Q4. For each lender-year, we construct the ratio of the number of green, brown, and neutral to total deals, respectively (*deals ratio*). We also construct the same ratios weighted by deal value (*value ratio*). For the energy sub-sample, we construct these ratios based on renewable to total renewable and fossil fuel deals. These deal ratios and value ratios are the outcome variables in our key regressions. Additionally, we analyze the loans directly in quarterly loan-level regressions.

3.3 Equator Principles

We obtain a list of members of the EP Association (EPA) from the EP website, including their join date.[15] We manually select the lender parent IDs in Dealscan that match these lenders based on the lender names.

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

3.4 Descriptive Statistics

PF is of key importance for the green transition. Projects are often related to energy and infrastructure, as shown in Panel A of Figure 1. energy accounts for more than sixty percent of the PF syndicated loan market in most years. Within these key industries, Panel B shows that energy deals are usually green or brown. This is expected, since these are often either renewable or fossil focused. The PF market is a large part of renewable energy financing. 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. Infrastructure is often classified as neutral, consistent with such projects having neither a clear negative nor positive environmental impact.

Table 1 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 is 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.

Figure 2 shows that the PF market is very skewed towards large lenders. To ensure that our analysis is not biased by small lenders that do not affect the market much, we use a weighted regression for our analyses at the lender-year level. The weights for these regressions are based on the number of deals in that lender-year.

Figures 6 and 7 in Appendix A.2 plot the development of the market share of treated versus control lenders split by deal greenness.

4 Lender-Level Analyses

We run multiple analyses to test the impact of EP4. In this section, we focus on the greenness of lender portfolios by running Difference-in-Differences analyses around the introduction of EP4. We test whether post-EP4, EPFIs finance more renewable energy deals in the renewable and fossil energy sub-sample, and more broadly green, neutral, or brown projects based on 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 countries. Treat equals 1 when lender i is an EP member before EP4 is implemented, and 0 otherwise. Post is 1 from October 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 weight each observation by the number of deals by a lender in a year.

Table 2 reports the results from these regressions. We hypothesize that treated lenders reduce brown loan origination after EP4. However, we find no evidence supporting this hypothesis. In column (1), the dependent variable is the *renewable 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 *renewable value ratio*. In both columns, the coefficient estimate on the interaction term $Treat \times Post\ EP4$ is statistically insignificant. The coefficients are also quantitatively small and flip sign between specifications.

Columns (3)–(8) of Table 2 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 sign between the specifications. This indicates that, 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.

Overall, the results based on different classifications paint a consistent picture. The introduction of EP4 did not lead EPFIs to shift lending to more environmentally-friendly projects compared to non-EPFIs. In the remainder of this section, we focus on the GPT-based classification. This enables us to use the full sample and maintain greater statistical power evidenced by the smaller standard errors in Table 2. Additional results based on the energy sub-sample are reported in Appendix A.2 Figure 9.

4.2 Parallel Trends

It could be that our main coefficient is biased towards zero because pre-trends offset the treatment effect. We test the corresponding parallel trends assumptions in a dynamic DiD with separate coefficients for each period before and after EP4, dropping period -1. Figure 3 documents these results. While some pre-treatment coefficients are statistically different from zero, there are no clear pre-trends. The most striking result is in period $+1$, with a spike in neutral value and a decrease in green value. 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, we find no evidence that the implementation of EP4 affects the greenness of credit allocation.

4.3 Robustness and Model Risk

We estimate many variations of the key regressions to ensure that our results are not the result of a specific model specification. Specifically, we identify seven modelling choices that we made and test alternative options:

1. Late EP updates. In the benchmark setting, all lenders that join the EP before EP4 are defined as treated and all others are control lenders. We alternatively drop lenders that join

after EP4 and lenders that leave the EP in 2022 or 2023.

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 × time. We consider the following alternatives: lender; lender and time; lender and lender size bucket × time; lender and lender region × time; lender, lender size bucket × time, and lender country × time; lender, lender size bucket × times, and lender region × time.

4. Frequency. The main analysis is on annualized data. As an alternative, we consider quarterly frequency.

5. Geography. The benchmark includes all projects globally, which aligns with the climate risk assessment requirements in EP4. Alternatively, we drop projects in certain regions. We run 'non-US', 'non-EU', 'EU', 'designated countries', and 'non-designated countries'. Designated countries are defined by the EP as members of the OECD that are on the World Bank High Income list.

6. 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.

7. Lender size filters. 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. As an alternative, we run unweighted regressions including all lenders or the subset of large lenders determined as lenders with at least 10 deals in the four years pre-sample or at least 10 deals in-sample.

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 22 specifications for each outcome variable or a 132 specifications that we implement for all outcome variables as in our benchmark settings in Table 2. 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 output. Out of the 132 specifications, only five are statistically significant at the 5% level. These statistically significant results are concentrated in regressions that use the neutral deals ratio as dependent variable (see Panel C).

In Figure 4 we restrict the number of model specifications to 132 in order to cleanly illustrate the effects of deviations from our benchmark model. We now take a step further by testing all combinations of the potential modelling choices listed above. In total, this gives us $2 \times 7 \times 2 \times 6 \times 5 \times 4 \times 2 = 6720$ specifications that we select for each outcome variable. 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. The mean for the neutral ratios may be slightly above zero. The mean for brown is slightly negative, but all these results clearly indicate that irrespective of modelling choices, we cannot detect a consistently significant effect of EP4 on green, brown, or neutral lending.[16]

Overall, 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., Forthcoming). We therefore conclude that EPFIs do not shift from brown to green lending compared to other lenders after the implementation of EP4.

5 Loan-Level Analyses

The lender-level regressions show that lenders do not make more green loans after EP4. However, there could be confounding changes to the demand for brown funding that correlate with the lending activity of EPFIs and offset potential treatment effects on the lender-portfolio level. In this section, we move to loan-level analyses to control for these effects.

[16] Similar scatter and density results for the sub-sample analysis on renewable and fossil fuel energy projects are available in Figure 9 in Appendix A.2.

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.

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

where $Greenness_{i,t}$ is a dummy for whether a project 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, 0 for brown loans. $Treat$ is 1 when a loan is at least 10 mln USD and an EPFI is part of the consortium. Post is 1 from October 2020, with the start date of EP4. We include a range of different fixed effects, which we abbreviate as $FE_{i,t}$ 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 characteristic, 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.

Table 3 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 3. 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. However, given the low statistical significance and flipping of sign across columns, we conclude that the share of non-brown loans is not affected by EP4.

5.2 Loan-Level Triple-Differences

Even if the share of brown loans does not decrease after EP4, it may be that these loans change in other dimensions. Therefore, we implement a triple-difference design to test whether non-brown treated loans become larger or receive longer maturities. We focus on the full sample using the GPT-based project classification for the remainder of this section. The regression specification is as follows:

$$Y_{i,t} = FE_{i,t} + \beta Treat_i \times PostEP4_t \times Non - Brown_{i,t} + \epsilon_{i,t}, \qquad (3)$$

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 4 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 differential impact on brown versus non-brown loans.

5.3 Robustness

For each of the specifications in columns (2) to (6) of Table 3 Panel B and Table 4, we run 15 alternative specifications to test the robustness of our loan-level results. Specifically, we run the same regression with five different greenness classifications from the GPT model, and we use three different treatment definitions. In the benchmark setting, a loan is treated when there is EPFI involvement and the loan is larger than 10 mln 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 we included above, there are 75 specifications for the DiD and both triple differences. Figure 8 in Appendix A.2 documents the coefficient of interest and the corresponding t-statistics for these robustness tests. The null-results in the loan-level output are robust to these variations in modelling choices.

6 Limitations

There are two remaining concerns with our analysis. First, our null-results may not be explained by the lack of impact of climate risk management, but by potential non-compliance of EPFIs. In Section 2, we discuss that EPFIs have incentives to implement climate risk assessments properly, since the results of these assessments are partially disclosed. Of course, it remains possible not to implement the EP framework very diligently, as it is a voluntary commitment without strict sanctions for non-compliance. We cannot rule out that our null-results are explained by non-compliance, since we do not observe it. However, the conclusion that there is no causal impact from setting climate risk management standards in the EP framework on the greenness of loan origination remain valid even then.

Second, it could be that EP4 impacts the greenness of brown loans, instead of the size of the brown loan portfolio. For example, enhanced climate risk management could improve the brown projects that EPFIs support. This could result in climate additionality when the EPFI requires greener project development within brown projects, or it could be about mitigating climate risk within these projects better. While important, this is currently outside the scope of this paper. Therefore, we remain agnostic about the overall effectiveness of the EP and, more broadly, voluntary green pledges. We solely conclude that we do not observe increased non-brown origination.

7 Conclusion

Many lenders make voluntary green pledges. It is important to understand whether such voluntary initiatives result in greener loan origination. We analyze this in the PF market, which is of key importance for the green transition. PF allows us to measure green versus brown lending relatively cleanly because loans support single-purpose developments. Project descriptions offer information of the expenditures financed with PF loans, which is often unobserved in other settings.

Our analysis focuses on the EP, a specific green pledge focusing on risk management 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. This setting allows us to disentangle the effect of a lender's sign-up decision from the effect of the green pledge itself. To the best of our knowledge, we are the first to quantify the causal impact of a voluntary green pledge on the greenness of credit allocation.

Using a simple keyword-based classification, we find that EPFIs do not move faster from fossil to renewable energy projects after the introduction of EP4. Consistent with this result, in the full sample of loans and based on a classification using OpenAI's GPT-4 model, we find that EPFIs do not move faster from brown to green or neutral projects. In additional loan level analyses, we document that the share of affected renewable energy or broader non-brown loans does not change after EP4, nor do these non-brown loans become larger or receive longer maturities. We confirm that these results are robust when we control for demand effects. Our results are also robust to model risk, since they remain similar in a wide range of plausible model specifications. We do not find any evidence supporting causal impact from EP4 on the greenness of loans.

Our findings have immediate policy relevance. We document that voluntary green pledges do not have to cause greener credit allocation. If policymakers wish to incentive green lending, they may have to take a step beyond supporting voluntary commitments by lenders. For example, regulations such as additional capital requirements for brown loans may be required.

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Table 1: 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. EPFI 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
EPFI	Dummy	Lender x Year	631	0.930	1.000	0.255	3206	0.011	0.000	0.105
Post EP4	Dummy	Lender x Year	631	0.377	0.000	0.485	3206	0.343	0.000	0.475
Number of deals	n	Lender x Year	631	15.513	7.000	21.947	3206	2.859	1.000	4.205
Renew deals ratio	[0-1]	Lender x Year	560	0.662	0.716	0.331	2119	0.674	1.000	0.433
Renew value ratio	[0-1]	Lender x Year	560	0.613	0.649	0.361	2119	0.656	1.000	0.446
Green deals ratio	[0-1]	Lender x Year	631	0.436	0.455	0.298	3206	0.438	0.333	0.435
Green value ratio	[0-1]	Lender x Year	631	0.400	0.364	0.318	3206	0.419	0.232	0.442
Neutr deals ratio	[0-1]	Lender x Year	631	0.245	0.200	0.254	3206	0.223	0.000	0.359
Neutr value ratio	[0-1]	Lender x Year	631	0.241	0.169	0.271	3206	0.226	0.000	0.370
Brown deals ratio	[0-1]	Lender x Year	631	0.319	0.286	0.284	3206	0.338	0.000	0.417
Brown value ratio	[0-1]	Lender x Year	631	0.360	0.337	0.314	3206	0.355	0.000	0.431

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 2: 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. In the first two columns, we restrict the sample to renewable and fossil energy projects. The outcome variable is the ratio of renewable 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 × Post EP4 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. 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.

	Renewable Ratios		Green Ratios		Neutral Ratios		Brown Ratios	
	Deals	Value	Deals	Value	Deals	Value	Deals	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post EP4	0.0133	-0.0110	-0.0267	-0.0547	0.0313	0.0463	-0.0046	0.0084
	(0.0513)	(0.0566)	(0.0330)	(0.0439)	(0.0221)	(0.0442)	(0.0224)	(0.0221)
Fixed-effects								
Lender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Country x Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,679	2,679	3,837	3,837	3,837	3,837	3,837	3,837
R^2	0.80146	0.78899	0.73698	0.70595	0.66249	0.63550	0.74472	0.71936

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

Table 3: 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 EPFI 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	0.00751	0.50135	0.50784	0.75945	0.69443	0.94205

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	0.00191	0.36468	0.36973	0.59945	0.63436	0.92987

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

Table 4: 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 EPFI 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	0.16577	0.55399	0.56079	0.73274	0.64544	0.98492

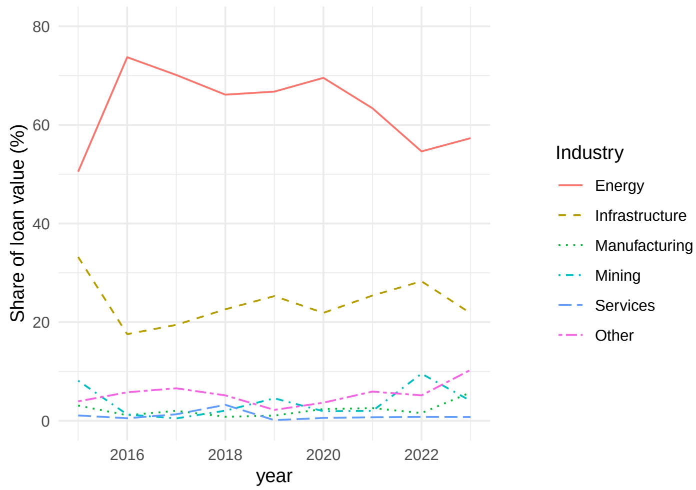
Panel B: Loan Maturity

	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	0.07870	0.48217	0.49258	0.73574	0.60512	0.92778

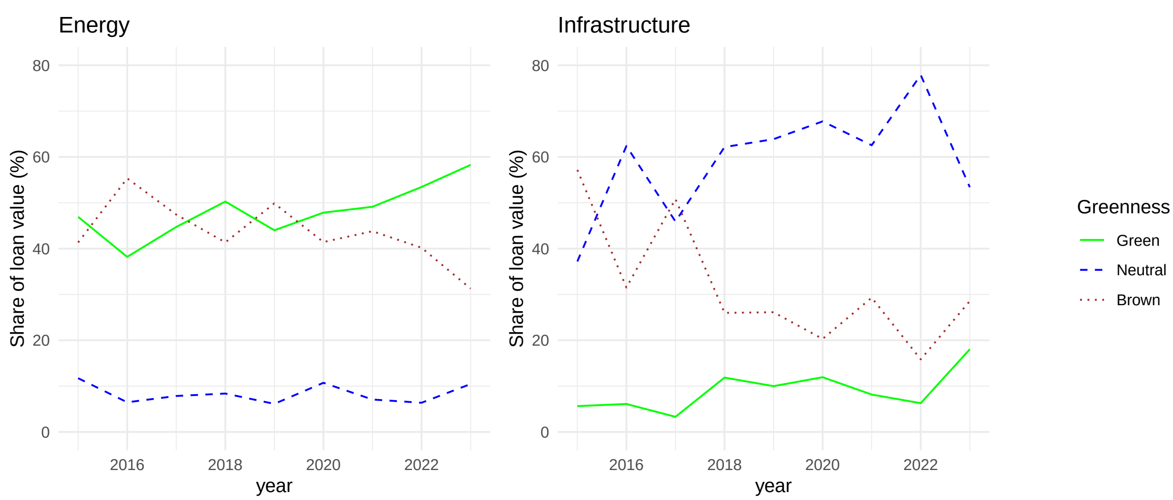
*IID standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

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

Panel A: Industry Distribution of Loans

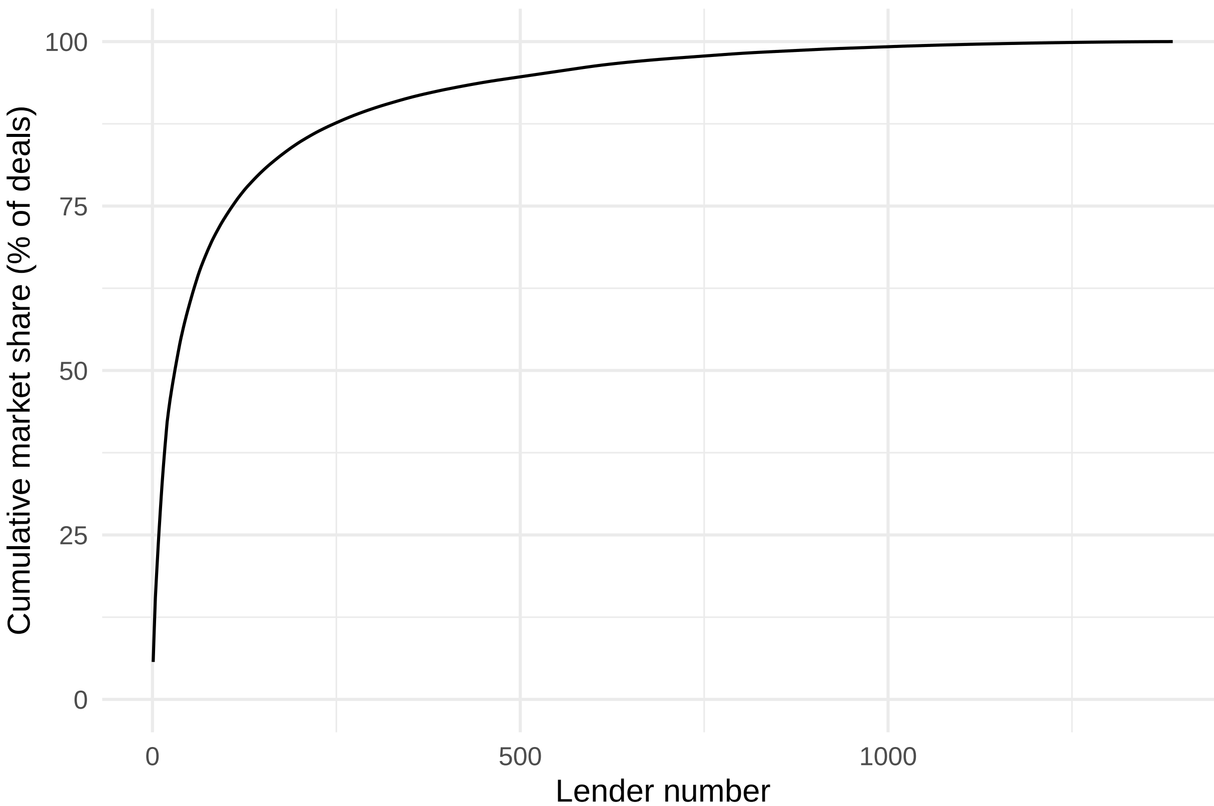


Panel B: Greenness of Loans within Industries



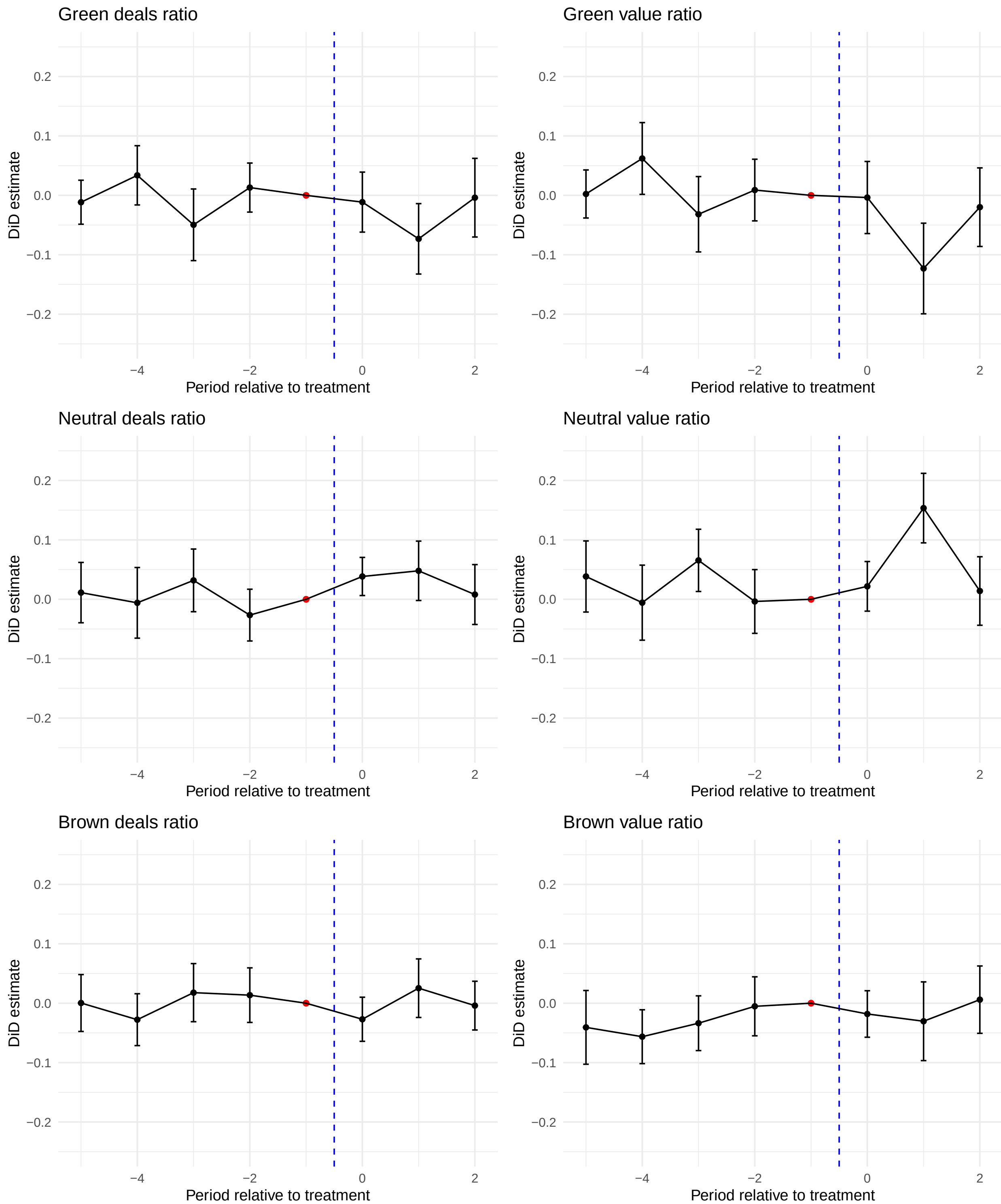
Panel A shows the share of value in project finance industries over time. Industries are based on project sectors reported by DealScan ('project_finance') manually grouped into broader categories. energy includes fuels and pipelines, and infrastructure includes construction and buildings. Panel B documents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

Figure 2: Lender Size Distribution



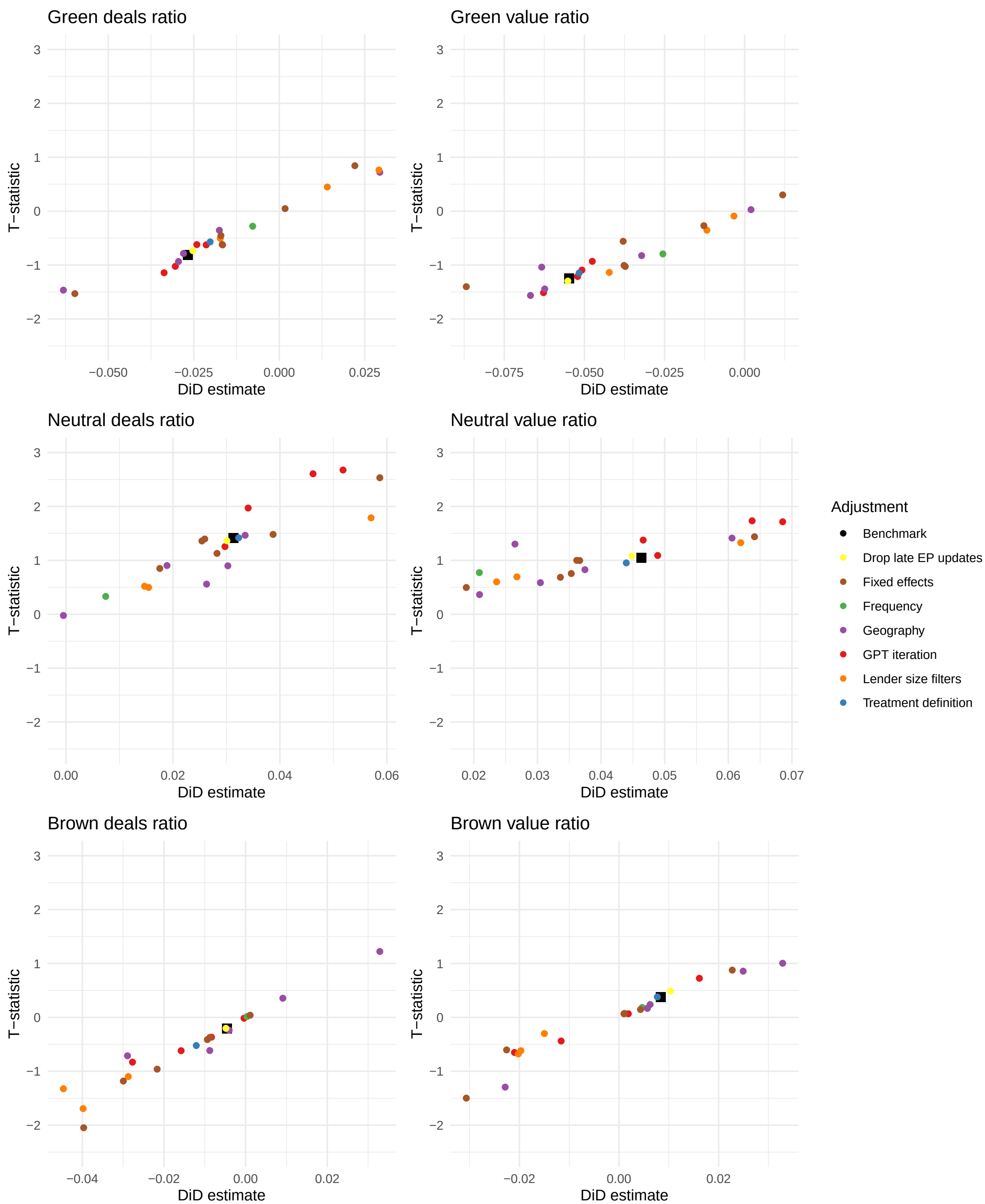
This figure shows the cumulative market share of the largest X lenders based on all project finance deals in our sample from 2015Q4 until 2023Q3.

Figure 3: Parallel Trends for Lender-Level Difference-in-Differences of Greenness Ratios



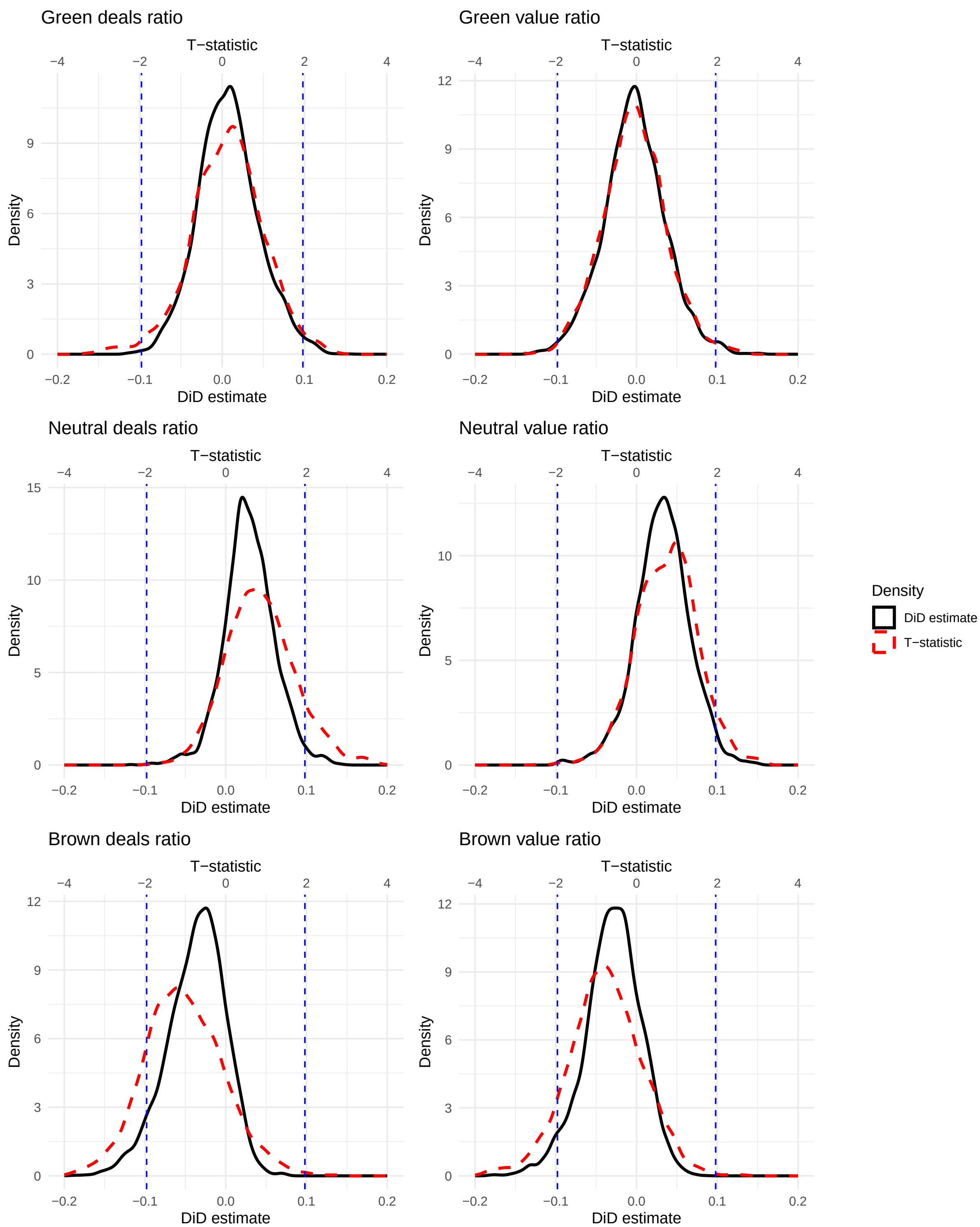
This figure presents the coefficients and 95% confidence interval from a dynamic DiD model corresponding to the lender-level DiD shown in Table 2. We regress the lender-level ratios of green, brown or neutral to total deals or values, respectively on a set of Treat $\times$ Period dummies and include 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. 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 2, 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 2. This figure includes all possible combinations of sample and model specifications described in Section 4.3, a total of 6720 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.

A Appendix

A.1 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 it's "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
> - 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 5: 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

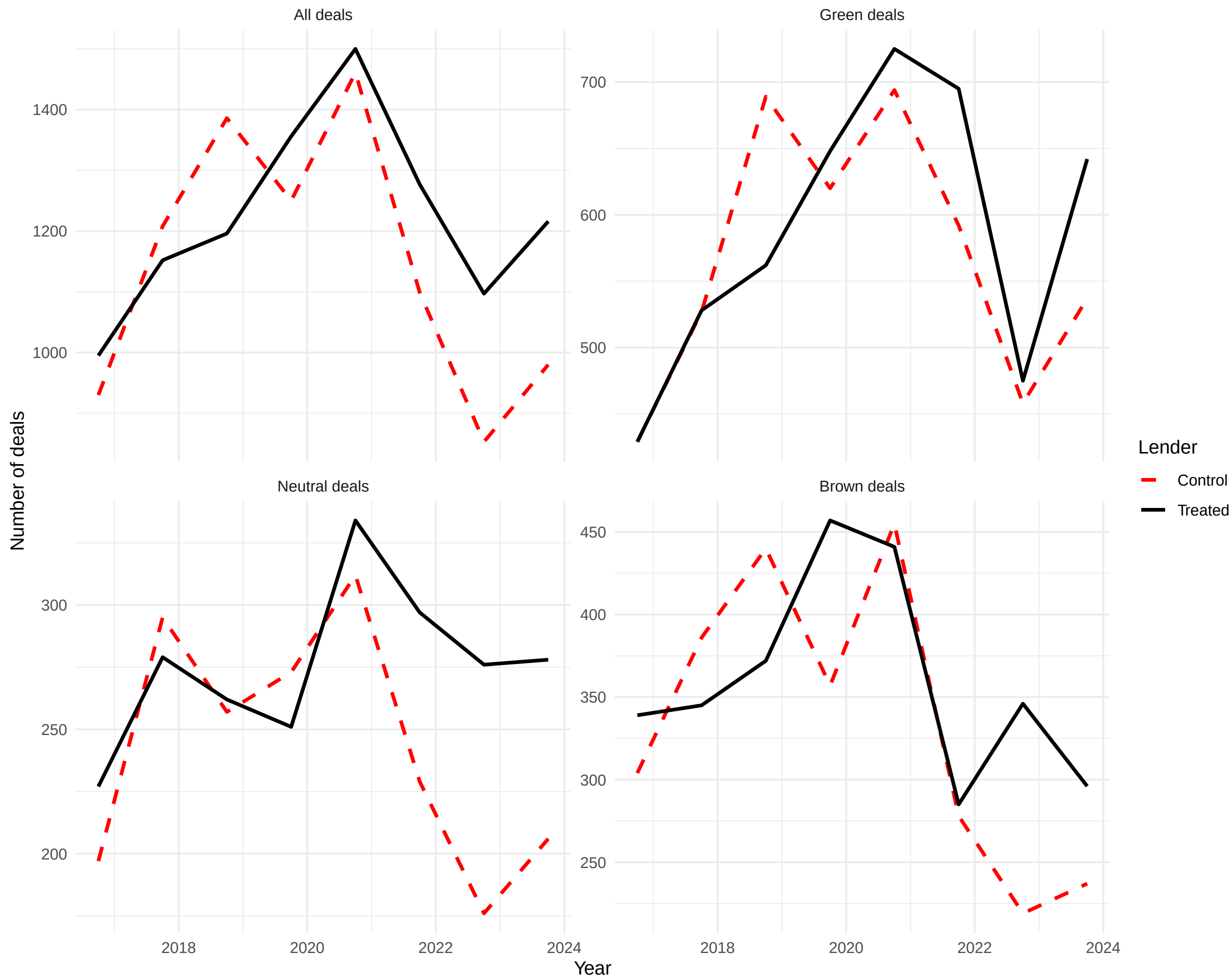
A.2 Additional Output

Table 6: 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

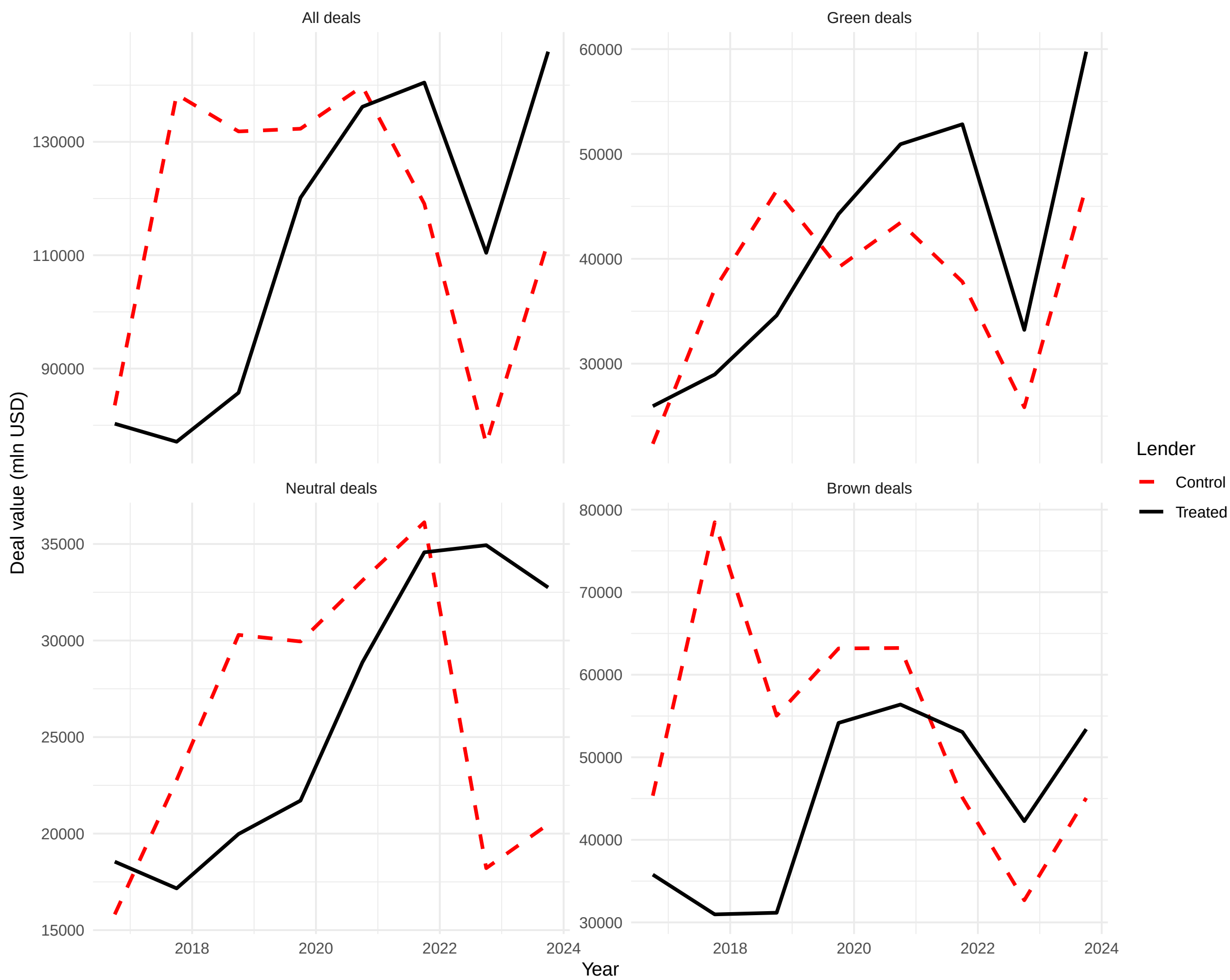
Loan variables	**Definition**	**Source**
Treat	Dummy; 1 if loan is larger than 10mn USD (deal_amount_converted) and from 2020Q4.	DealScan
Post EP4	Dummy; 1 from 2020Q4	
Treat intensity	[0-1]; 0 if loan is smaller than 10mn USD. Otherwise, number of EP lenders divided by total number of lenders.	DealScan + 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

Figure 6: Number of Deals by Treated versus Control Lenders, Split by Greenness



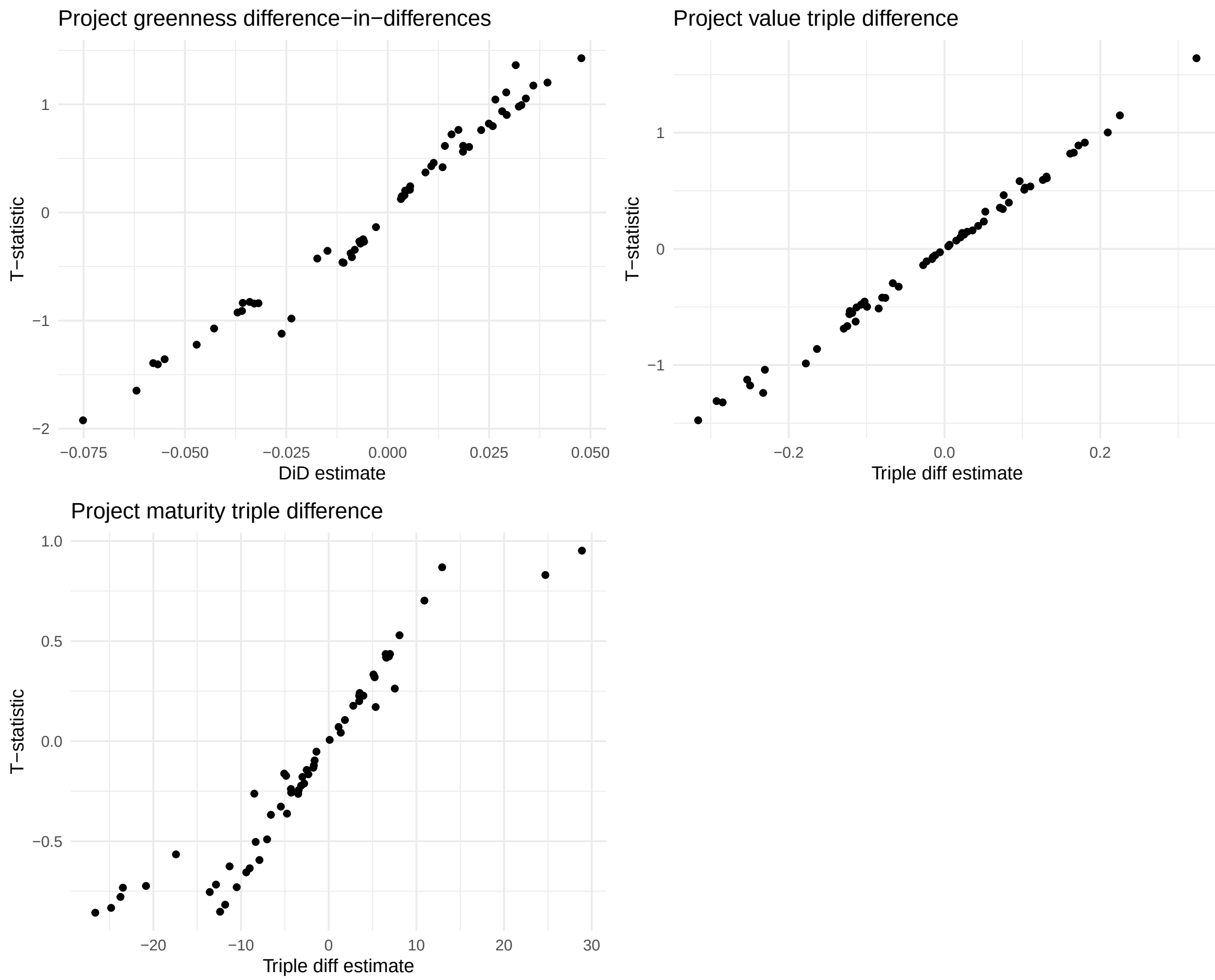
This figure shows the deal involvement by treated versus control lenders, split by greenness of the project. Lenders are treated when they are EP members before EP4. When more than one lender is involved with a deal, the deal is attributed to all lenders; thus, there is double-counting. This construction aligns with the construction of the key output variables of the lender level difference-in-differences regressions. 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: Loan Value by Treated versus Control Lenders, Split by Greenness



This figure shows the value (mln USD) committed by treated versus control lenders, split by greenness of the project. Lenders are treated when they are EP members before EP4. 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.

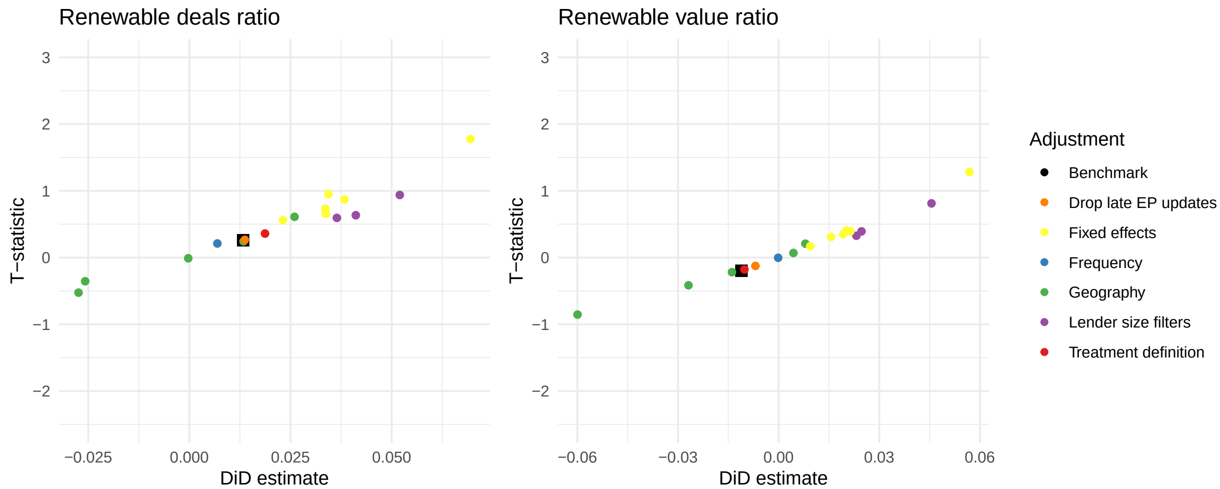
Figure 8: Scatter of Coefficients and T-Statistics of Loan-Level Difference-in-Differences and Triple-Differences



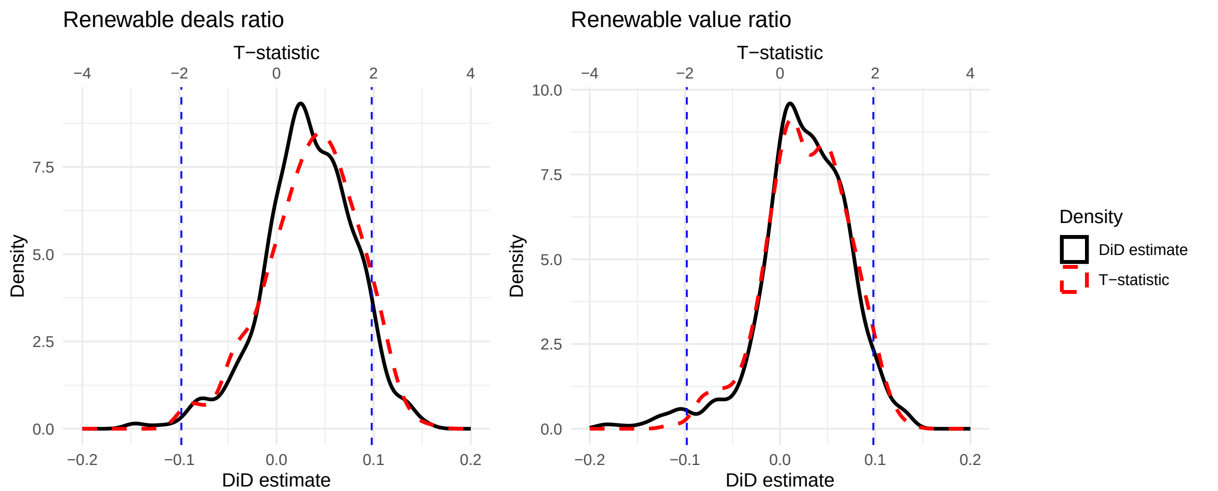
This figure shows the coefficients and t-statistics of alternative specifications for the project level DiD and triple-diff analyses from Tables 3 and 4. Variations from the benchmark settings are described in Section 5.3. The top left panel presents variations of the DiD analysis about the share of non-brown loans after EP4. We regress the loan level non-brown dummy on the treatment by EP4. The top right and bottom panels present variations of the triple-diff analyses on the non-brown loan size and maturity after EP4, respectively. We regress the loan size (log(value in mln USD)) or maturity (in months) on Treat × Post EP4 × 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.

Figure 9: Distribution of Coefficients and T-Statistics of Difference-in-Differences on Lender-Level Renewables Ratios

Panel A: Scatter of Coefficients and T-Statistics of DiD on Lender-Level Renewables Ratios



Panel B: Density of Coefficients and T-Statistics of DiD on Lender-Level Renewables Ratios



This figure shows the coefficients and t-statistics for variations of the lender-level DiD models in columns (1)–(2) of Table 2. 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 2 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.