The unintended consequences of climate policy:

Carbon taxes, regulatory arbitrage, and competition in lending

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Abstract

This paper examines how carbon taxation affects the allocation and pricing of syndicated bank credit across borders. Using a global sample of loans from 2002 to 2022 and a stacked difference-in-differences design, we find that carbon taxes reduce the carbon intensity of foreign loan portfolios by approximately 14 to 21 percent, reflecting credit reallocation rather than higher loan spreads. Domestic lenders expand market share following tax adoption, while foreign lenders retrench unless similar taxes are in place in their home countries. We document heterogeneity across borrowers based on emissions intensity, climate change exposure, and national environmental regulation, with foreign lending exhibiting systematically different adjustment patterns. Overall, the results show that carbon taxes can materially decarbonize loan portfolios without raising borrowing costs, but their global effectiveness depends on cross-country policy alignment and lender portfolio adjustments.

JEL codes : G21, G28, Q58, G32, Q54.

Keywords: bank loans; carbon emissions; climate regulation; lending; bank risk; loan allocation; carbon taxes

1. Introduction

Financial intermediation increasingly operates under the constraints of climate policy. Among these, carbon taxes have emerged as a cornerstone of transition strategy, designed to internalize environmental externalities and incentivize low-carbon investment. Yet despite their policy rationale, carbon taxes also transmit through credit markets, influencing how banks allocate and price capital across borders. This paper examines how syndicated lenders adjust loan allocation, pricing, and portfolio composition in response to the introduction of carbon taxes, with a particular focus on lead arrangers and the heterogeneity of borrowers' environmental profiles.

Classical models of delegated monitoring predict that lenders mitigate information frictions by retaining exposure to opaque borrowers (Diamond, 1984; Holmström and Tirole, 1997; Sufi, 2007). In syndicated lending, this role is concentrated in lead arrangers, who design contracts, screen borrowers, and monitor performance. Recent evidence, however, shows that arrangers increasingly reduce their retained exposure after origination without degrading loan outcomes (Blickle et al., 2022). This shift implies that information intermediation can operate through screening, contract design, and syndicate composition rather than through balance-sheet commitment alone. Against this backdrop, carbon taxation offers a sharp setting to examine this mechanism. The introduction of a tax raises uncertainty about borrowers' future cash flows and regulatory compliance, particularly for emissions-intensive firms. Whether lead arrangers respond by repricing risk, reallocating credit toward cleaner borrowers, or adjusting their retained exposure provides insight into how climate policy reshapes delegated monitoring.

Building on this perspective, we study how national carbon taxes reconfigure the allocation of risk and monitoring within syndicated lending markets that span borders. Carbon taxes do not affect all lending relationships symmetrically: they alter borrower risk profiles while also interacting with differences in regulatory regimes between lender and borrower countries. This creates scope for heterogeneous responses in domestic and foreign lending.[1] Accordingly, we focus on how lending portfolios adjust across borders and across borrower types.

Using syndicated loan data from DealScan merged with firm-level carbon intensity from S&P Global's Trucost, and employing a stacked difference-in-differences framework, we show that the adoption of a carbon tax in a borrower's country leads to a pronounced reallocation of credit toward less carbon-intensive firms, particularly in foreign lending. Our global dataset allows us to quantify the scale of post-tax adjustment. Following the implementation of a carbon tax, lenders reduce the carbon intensity of foreign loans by approximately 3.1 to 4.7 metric tons of CO_2 per million U.S. dollars of revenue, an estimated 14% to 21% decline that is both statistically and economically meaningful. Dynamic event-study estimates confirm that the largest adjustment occurs immediately upon tax adoption in carbon intensity, with no evidence of anticipatory behavior, supporting our identification strategy.

Although carbon taxes strongly influence portfolio reallocation, their direct impact on pricing is small (an insignificant increase of about 2.3 basis points). In contrast, the EU ETS is associated with a substantial 30 basis-point increase in loan costs, equivalent to approximately a 19% increase, suggesting that cap-and-trade regimes primarily operate through risk repricing rather than portfolio adjustments. Together, these results show that carbon taxes and ETS mechanisms affect cross-border lending through distinct yet complementary channels: taxation drives portfolio realignment, while cap-and-trade systems increase the cost of credit for emissions-intensive borrowers.

[1] In our carbon-tax setting, foreign lending refers to loans where the borrower is domiciled in a carbon-tax country and the lender is domiciled abroad. Domestic lending refers to loans where the lender and borrower are domiciled in the same country that has imposed a carbon tax.

We further show that the response of syndicated lending to carbon taxation is consistent across measures constructed from textual indicators of climate policy attention, realized emissions profiles, and regulatory environments. When we use text-based measures of regulatory exposure, we observe a decrease in carbon intensity for the most heavily exposed firms after a tax is introduced. Likewise, when we classify borrowers by their industry based on pollution levels, the strongest carbon adjustments occur among borrowers at the very top of the emissions distribution, echoing recent evidence that a small set of "super-emitters" drive much of the variation in environmental outcomes. However, when we examine foreign loans, we observe that the largest emissions reductions shift towards the center of the emissions distribution, with the result being consistent across measures based on discourse about climate change and industry-level carbon emissions intensity.

A third dimension - country-level biodiversity policy - adds context to these patterns. Biodiversity policy is not directly related to borrower emissions; however, the post-carbon tax decline in carbon intensity is weaker in countries with stronger ecological protections. This suggests that carbon and ecosystem policies interact in shaping the credit environment, even though biodiversity rules alone do not alter lending outcomes. Together, these findings show that the impact of carbon taxation on the geography and intensity of syndicated lending depends on borrowers' operational emissions characteristics and national policy settings.

We further document that foreign lenders withdraw from carbon-taxed jurisdictions, reducing their cross-border portfolio shares within three years of policy implementation. Domestic lenders partially offset this retrenchment by expanding local lending, suggesting a substitution effect consistent with competitive repositioning and regulatory arbitrage. When both lender and borrower countries adopt carbon taxes, these offsetting effects largely dissipate, indicating that international policy coordination reduces arbitrage incentives. This evidence extends and complements prior work by Benincasa (2021), Benincasa et al. (2022), and Laeven and Popov (2023), who examine one-directional or single-policy effects across markets.

The contrast between traditional models that emphasize exposure retention by the informed lender to mitigate information asymmetry (Diamond, 1984; Townsend, 1979) and newer evidence emphasizing screening and redistribution (Blickle et al., 2022) motivates another central question of this paper: do lead arrangers confronted with climate-policy risk retain greater exposure to high-emission borrowers, or do they rely on more intensive ex ante screening and portfolio reallocation, particularly across borders, to manage transition risk efficiently?

A distinctive contribution of our study is the ability to measure how lead arrangers adjust their effective loan exposures after origination in response to a carbon-tax shock. Unlike prior studies that treat syndicate structures as static (Dennis and Mullineaux, 2000; Ivashina, 2009), we estimate the lead bank's predicted post-origination holding share using the methodology of Blickle et al. (2022) and link these estimates to borrower-level carbon intensity. This dynamic framework reveals how lead arrangers manage secondary market exposure when confronted with climate policy risk.

Earlier research documents a "carbon premium" in loan spreads for high-emission borrowers (Chava, 2014; Ehlers, Packer, and De Greiff, 2022), but it assumes that syndicate composition is fixed. Relaxing that assumption, we show that arrangers actively reallocate exposure and reprice risk in response to new regulatory regimes. They mitigate climate-related information asymmetry not by holding greater exposure to carbon-intensive firms, but by employing enhanced ex-ante due diligence and pricing mechanisms that enable efficient risk transfer without increasing loan costs. At the same time, both carbon intensity and loan costs are significantly and positively associated with the lead arranger's share of the deal, suggesting that when loans are perceived as riskier (due to higher emission intensity), lead arrangers retain larger positions and charge a higher spread, consistent with information asymmetry theories. This interpretation reframes climate-risk management in syndicated lending: rather than merely bearing the risk of high-emission borrowers, lead arrangers manage it through information and screening advantages that substitute for balance-sheet exposure. Our results complement Drucker and Puri (2009), Blickle et al. (2022), and Delis et al. (2023) by demonstrating that arrangers' informational advantages extend to climate policy shocks, where proactive screening drives the efficient allocation of carbon-related credit risk.

Taken together, these findings depict a nuanced adjustment process. Carbon taxes reduce financed emissions but create cross-border distortions: foreign lenders retrench while domestic banks expand with limited pricing power, and environmentally proactive lenders drive most of the decarbonization through selective screening. Such heterogeneous responses indicate that unilateral climate policies can realign global credit flows without uniformly greening the finance sector.

Our study contributes to four strands of research. First, it advances theories of information intermediation in syndicated lending by showing how arrangers manage transition-risk shocks through screening rather than exposure retention (Holmström and Tirole, 1997; Sufi, 2007; Blickle et al., 2022). Second, it contributes to the climate-finance literature by demonstrating how carbon taxes and ETS regimes jointly shape loan allocation and pricing across borders (Bolton and Kacperczyk, 2021; Ehlers et al., 2022; Pástor, Stambaugh, and Taylor, 2021). Third, it adds to the work on cross-border banking and regulatory arbitrage (Houston, Lin, and Ma, 2012; Benincasa et al., 2022; Laeven and Popov, 2023) by showing how environmental-policy heterogeneity reallocates capital between domestic and foreign markets. Finally, it enriches emerging research on biodiversity finance (Giglio et al., 2023; Flammer et al., 2025) by documenting the interactions between biodiversity regulation and carbon taxes in lending outcomes, particularly the carbon intensity of lending, and illustrating spillovers in environmental risk pricing in bank portfolios. More broadly, these findings illustrate the shortcomings of uncoordinated climate finance policies. In the absence of harmonized carbon taxation, lenders can reallocate emissions risk across borders rather than mitigate it, blunting the effectiveness of national climate initiatives. By revealing how borrower heterogeneity and international policy asymmetry jointly shape the decarbonization of credit, this paper clarifies both the potential and the unintended consequences of using financial intermediation as an instrument of climate transition.

2. Background and Motivation

2.1 Related Literature

Recent research documents that climate policy increasingly shapes credit allocation and pricing through banks' responses to transition risk. A growing body of evidence shows that lenders incorporate borrower emissions and regulatory exposure into loan terms. Ehlers, Packer, and De Greiff (2022) show that syndicated loan spreads vary with borrower carbon intensity, while Delis et al. (2024) document that banks price the risk of stranded fossil-fuel assets into loan contracts. These studies establish that climate policy and emissions exposure are financially material in bank lending, but they largely abstract from how lending portfolios adjust across borders or over the life of syndicated loans.

Our paper is most closely related to Laeven and Popov (2023), who show that carbon taxes induce capital reallocation away from carbon-intensive sectors, with pronounced effects on cross-border lending. Their analysis emphasizes regulatory arbitrage, where banks shift their exposure toward jurisdictions with looser climate policies, thereby limiting the effectiveness of unilateral regulation. We complement and extend their findings in three dimensions. First, we study a broader universe of borrowers rather than focusing on fossil-fuel lending. Second, we explicitly distinguish between portfolio reallocation and loan repricing. Third, we show that foreign and domestic lenders adjust along different margins, with foreign lenders reallocating within the emissions distribution rather than exiting the highest-emitting firms outright.

This cross-border dimension connects our work to studies of climate-policy spillovers in international banking. Benincasa (2021) and Benincasa, Kabas, and Ongena (2022) show that differences in national climate policies generate lending spillovers, allowing banks to shift exposure rather than finance emissions reductions. Their evidence illustrates how policy heterogeneity undermines unilateral climate action. We extend this literature by showing that these spillovers operate not only across countries but also across borrower types within countries, depending on emissions intensity, climate policy exposure, and the broader environmental regulatory environment.

More broadly, our analysis contributes to the literature on regulatory arbitrage and cross-border banking. Prior work shows that banks adjust lending geographically in response to differences in regulation, capital requirements, and institutional quality (Popov and Udell, 2012; Giannetti and Laeven, 2012; Avdjiev, Aysun, and Hepp, 2019). We show that climate policy adds a new dimension to this mechanism: carbon taxes reshape not only where banks lend, but also which segments of the emissions distribution they finance, with distinct responses by domestic and foreign lenders.

A related strand examines how information frictions and monitoring shape syndicated lending. Classical models predict that informed lenders retain exposure to mitigate moral hazard (Diamond, 1984; Holmström and Tirole, 1997; Sufi, 2007). Recent evidence challenges this view.

Blickle et al. (2022) show that lead arrangers frequently reduce their retained shares after origination without impairing loan performance, indicating that screening and syndicate structure can substitute for balance-sheet commitment. Our study builds on this insight by showing that arrangers confronted with climate-policy shocks manage transition risk primarily through screening and portfolio reallocation rather than by retaining exposure to high-emission borrowers.

Our borrower-level heterogeneity results relate closely to research showing that environmental outcomes are driven by a small subset of firms. Crosignani, Osambela, and Pritsker (2025) show that "super-emitters" account for a disproportionate share of carbon risk in equity markets. Consistent with this view, we find that reductions in loan carbon intensity following carbon taxes are concentrated at the upper tail of the emissions distribution, although this margin shifts toward medium-high emitters in foreign lending.

While not focusing explicitly on regulatory arbitrage, Fard, Javadi, and Kim (2020) provide supporting evidence that environmental regulation is a priced risk factor in international markets. Using a cross-country sample, they show that more stringent environmental regulations are associated with higher loan spreads and narrower syndicate participation, driven by heightened environmental liability risk. The study illustrates that such risks increase bankruptcy likelihood and depress credit ratings, suggesting that lenders adjust both price and non-price loan terms in response to environmental policy stringency. Their findings support the interpretation of regulatory exposure as a financial liability and reinforce the view that environmental risks materially affect loan contracting.

Our findings also connect to asset-pricing evidence that emissions exposures are internalized through a discount rate channel rather than directly driving cash flows, in our context of syndicated lending markets. This funding parallels recent evidence from equity markets suggesting that investors incorporate emissions intensity into required returns (Bolton & Kacperczyk, 2021). Crosignani et al. (2025) show that stock-return exposure to emissions operates through a discount-rate channel linked to innovations in emissions intensity. Their findings imply that transitions in expected emissions should alter financing conditions, even when cash flows remain largely unaffected. This mechanism is consistent with our empirical setting, where carbon-tax adoption alters lenders' expectations of firms' regulatory exposure and, in turn, leads to portfolio shifts and repricing in syndicated lending. These mechanisms are consistent with our evidence that carbon taxes lead primarily to portfolio reallocation rather than higher loan costs, except under cap-and-trade regimes such as the EU ETS.

Finally, our paper contributes to the emerging field of research on biodiversity and environmental risk in finance. While biodiversity regulation is conceptually distinct from carbon policy, recent studies show that ecological risk is financially relevant (Giglio et al., 2023; Flammer et al., 2025). We add to this literature by showing that carbon taxes interact with broader environmental regulations at the country level, influencing how lenders rebalance loan carbon intensity, even when biodiversity policy does not directly target emissions.

Taken together, the literature suggests that climate policy affects credit through both pricing and portfolio channels, and that cross-border spillovers and information frictions shape how these effects materialize. Our study integrates insights from climate finance, cross-border banking, and syndicated lending by analyzing how syndicated loan portfolios respond to the introduction of carbon taxes. We provide causal evidence on how carbon-tax adoption affects the carbon intensity, pricing, and cross-border composition of syndicated lending, with heterogeneous responses across borrower emissions profiles and lender domicile. In doing so, we extend the literature on climate finance by linking regulatory events to observable shifts in bank behavior across multiple aspects of credit allocation and environmental performance metrics.

2.2 Motivation and Research Questions

Our study examines how national carbon taxes reshape syndicated lending behavior by altering credit allocation, portfolio composition, and cross-border exposure. Our framework draws on theories of delegated monitoring and information asymmetry (Diamond, 1984; Holmström and Tirole, 1997; Sufi, 2007), together with recent evidence that climate policy affects financial intermediation primarily through transition-risk reassessment and portfolio adjustment rather than uniform repricing of credit (Benincasa, 2021; Benincasa et al., 2022; Laeven and Popov, 2023).

The first question concerns how carbon taxation affects the distribution of credit across borrowers with different emissions profiles. The introduction of a carbon tax increases expected compliance costs and regulatory uncertainty for carbon-intensive firms, raising concerns about future cash flows and asset stranding (Delis et al., 2024; Ehlers et al., 2022). Lenders may respond either by charging higher spreads to compensate for these risks or by reallocating credit away from high-emission borrowers. Prior evidence from cross-border lending suggests that climate policy induces reallocation of capital rather than systematic repricing, particularly when regulatory heterogeneity creates scope for adjustment along the extensive margin (Benincasa et al., 2022; Laeven and Popov, 2023). Accordingly, we expect carbon-tax adoption to reduce lenders' exposure to higher-emission borrowers, lowering the carbon intensity of syndicated loan portfolios.

A second question addresses whether carbon taxation affects loan pricing. Climate policy may raise required returns if lenders price transition risk directly into loan spreads, consistent with evidence that borrower emissions and environmental regulation are financially material (Chava, 2014; Fard et al., 2020; Delis et al., 2024). At the same time, if lenders manage climate risk primarily through screening and portfolio rebalancing, pricing responses may be muted under carbon taxes, especially relative to cap-and-trade regimes such as the EU ETS (Ehlers et al., 2022). We therefore explore whether loan costs rise following carbon-tax adoption, and allow for the possibility that lenders may simultaneously reduce their exposure to carbon-intensive borrowers while adjusting the spreads on remaining loans.

A third question examines heterogeneity within the borrower emissions distribution. A growing body of literature shows that a small subset of firms accounts for a disproportionate share of aggregate emissions and climate-related financial risk (Bolton and Kacperczyk, 2021; Crosignani et al., 2024). If lenders manage transition risk efficiently, adjustments in credit allocation should be concentrated among these high-emission borrowers rather than uniformly distributed across firms. Thus, we explore whether carbon-tax–induced reductions in loan carbon intensity are concentrated in the upper tail of borrower emissions.

The final question concerns heterogeneity across lending relationships, particularly between domestic and foreign lenders. Differences in regulatory alignment, monitoring costs, and portfolio flexibility imply that foreign lenders may be more responsive to climate-policy asymmetries, reallocating credit across borders rather than maintaining exposure in newly taxed jurisdictions (Popov and Udell, 2012; Avdjiev et al., 2019; Benincasa, 2021). By contrast, domestic lenders may preserve borrower relationships while adjusting exposure through selective screening and pricing discipline. Our conjecture is that post–carbon tax reductions in loan carbon intensity are more pronounced in foreign lending than in domestic lending, reflecting stronger cross-border reallocation incentives.

Together, these research questions organize our empirical analyses around the informational, strategic, and geographic channels through which carbon taxation may influence syndicated lending. In particular, they emphasize portfolio reallocation, borrower heterogeneity, and cross-border regulatory asymmetries as the primary channels through which climate policy is transmitted into global credit markets.

3. Data and Methodology

3.1. Sample Construction

Our sample comprises syndicated loan data from Refinitiv LoanConnector DealScan database for the period from 2002 to 2022, merged with firm-level carbon intensity data from Trucost. We focus exclusively on syndicated loans, excluding Term Loan B facilities, as these are typically marketed to institutional investors and sold in the secondary market with limited retention by originating banks.

Our study focuses on the behavior of lead arrangers, the senior syndicate members responsible for negotiating loan terms, structuring deals, and assembling lending syndicates (Rajan,1992; Dennis and Mullineaux, 2000; Sufi, 2007). Lead arrangers typically retain the largest loan shares (Simons, 1993; Ivashina, 2009) and perform the monitoring and information intermediation functions that underlie the economics of syndicated lending (Panyagometh and Roberts, 2010; Lee and Mullineaux, 2004). They coordinate documentation, maintain communication with borrowers, and manage administrative duties throughout the life of the loan. Following prior studies that identify arrangers as the key informed agents in the syndicate (Ivashina, 2009; Berg, Saunders, and Steffen, 2016), we treat the lead arrangers as the effective "lenders" in our analysis.

We conduct the analysis at the deal level, consistent with established practices in the syndicated lending literature.[2] DealScan provides unique identifiers at the deal level, encompassing all related tranches. Deal-level analysis is the appropriate method to investigate syndicated lending in our case, as it captures the integrated structure of loan contracts and syndicate arrangements.

Since DealScan does not explicitly identify the lead arranger, we follow the approach of Sufi (2007) and Blickle et al. (2022) to identify the lead arranger.[3] If DealScan does not clearly indicate the lead arranger, we assign this role to the lender with the highest predicted share calculated following Blickle et al. (2022). The benefits of this approach are twofold. First, the innovation of our study is that we do not assume lead arrangers retain their initial holdings. The predicted shares reflect lenders' actual retained stakes after syndication, considering that arrangers frequently reduce their holdings post-origination. Second, our method avoids the common practice in prior studies of randomly assigning lead arrangers, thereby reducing potential misclassification bias.

We next match borrowing firms to their respective GVKEY identifiers using the DealScan-Compustat linking table provided by Chava and Roberts (2008). For lead arrangers, we utilize the mapping link from Schwert (2018) to connect DealScan lender names to the banking holding

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[2] For example, Sufi, 2007; Chaudhry and Kleimeier, 2013. Blickle et al. (2022) highlight that lead arrangers dynamically adjust their retained shares and respond strategically to loan-specific conditions post-origination, a behavior accurately captured through deal-level data rather than isolated tranche-level observations.

[3] Following Blickle et al. (2022), we first assign the lead arranger role to the lender designated as "Admin Agent." If no Admin Agent is identified, we select the lender holding one of the following titles: "Agent," "Bookrunner," "Joint Arranger," "Lead Bank," "Lead Manager," or "Mandated Lead Arranger." If none of these primary titles are present, we consider secondary titles such as "Co-Agent," "Co-Arranger," "Collateral Agent," "Coordinating Arranger," "Documentation Agent," "Managing Agent," or "Syndications Agent." When multiple lenders share lead arranger status within the same deal, we retain all co-lead arrangers, resulting in multiple lender-deal observations. Our analysis is therefore conducted at the lender-deal-year level, where deals may have multiple lead arrangers.

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companies' GVKEY identifiers in Compustat, focusing solely on lenders with at least 50 loans or a total loan volume of $10 billion. We employ a fuzzy matching algorithm to match the lenders not included in Schwert (2018).

After removing observations lacking either borrower or lender GVKEYs, our matched sample comprises 47,490 observations. We incorporate accounting data for both borrowers and lenders from Compustat Global. We obtain borrower firm-level carbon emissions data, based on Scope 1 CO_2 emissions from Trucost. Due to missing data for borrower and lender control variables, as well as key dependent and independent variables, the number of observations varies across regression specifications. Specifications that incorporate borrower carbon intensity (Scope 1 CO_2 emissions from Trucost) include 11,654 observations. Regressions that include loan costs from DealScan comprise 25,250 observations. The variation in sample sizes is consistent with prior literature that uses environmental and syndicated loan data (e.g., Delis et al., 2019; Kleimeier and Viehs, 2021). The sample construction steps are detailed in Appendix A1.

3.2. Variable Construction

3.2.1 *Countries with carbon tax*

We construct country-level carbon tax indicator variables for both borrower and lender countries, following Laeven and Popov (2023). First, we identify the countries of incorporation of borrowers and lead arrangers using the Compustat country identifier (FIC). $PostCT_{Borrower}$ is an indicator equal to one from the year a borrower's country adopts a carbon tax onward, and zero otherwise. Similarly, $PostCT_{Lender}$ is an indicator equal to one from the year a lender's country adopts a carbon tax onward, and zero otherwise. Appendix A3 lists the countries with carbon taxes, along with their implementation years.

3.2.2 *Classification of foreign and domestic loans, and loan shares*

We classify each lender–deal observation using the lender's country of incorporation from Compustat, and the borrower's country from DealScan. An observation is *foreign* if the lead arranger's domicile differs from the borrower's country, and *domestic* if they are the same. Accordingly, when we refer to a "foreign loan" (or "foreign lender"), we apply the foreign definition above; likewise, a "domestic loan" (or "domestic lender") follows the domestic definition above. For carbon-tax analyses, *'domestic'* denotes a lender and a borrower both in the country implementing the carbon tax, while *'foreign'* denotes a borrower in the carbon-tax country with a lender domiciled abroad.

Following Blickle et al. (2022), we construct foreign and domestic loan shares in three steps. First, we compute each lead arranger's USD exposure at the loan level using its predicted holding stake (Appendix A1). Next, we aggregate these exposures to the lender–borrower country-year level, collapsing multiple deals into weighted averages (with weights equal to each lender's predicted USD holding stake). Finally, for each lender–country–year, we sum USD exposures separately for foreign and domestic loans and label the resulting measures the foreign and domestic loan shares.

3.2.3 *Cost of loan*

We construct a lending cost measure to capture lenders' economic exposure to syndicated loans. At the tranche-year level, we calculate an exposure-weighted loan cost by multiplying DealScan's *all_in_spread_drawn_BPS* by each lender's predicted holding share, thereby capturing the effective spread associated with the lender's portion of the tranche. We then aggregate these tranche-level costs to the deal level by taking the average across tranches. To mitigate skewness and improve interpretability, the cost variable is log-transformed in the regression models.

3.2.4 *Carbon intensity*

We obtain firm-level carbon emissions data from S&P Global's Trucost, which provides annual Scope 1-3 emissions for publicly listed firms in advanced and major emerging economies, with coverage dating back to 2002. To measure borrower carbon intensity, we use Scope 1 greenhouse gas emissions scaled by borrower revenue, expressed as metric tons of CO_2 per $1 million of revenue. We then construct deal-level carbon intensity to capture environmental risk in syndicated lending, defined as an exposure-weighted average of borrower carbon intensity, weighted by each lender's share of the deal, at the lender–borrower–deal–year level.

We focus on Scope 1 emissions because OECD carbon-pricing metrics treat explicit (direct) carbon prices – carbon taxes and ETS – as charges on direct emissions (Scope 1) or on the carbon content of fuels, while indirect prices (e.g., electricity excise taxes and other implicit instruments) and Scope 2 emissions are treated separately (OECD, 2024, pp. 11–12). Trucost compiles carbon emissions data from company disclosures (e.g., reports submitted to Carbon Disclosure Project (CDP), annual and CSR reports, corporate websites) and supplements missing values using an input-output model consistent with the Greenhouse Gas (GHG) Protocol. Bolton & Kacperczyk (2021) and Aswani et al. (2023) provide thoughtful discussions on the appropriate use of carbon intensity measures, which support the use of carbon intensity (as opposed to overall carbon emissions) in our research design. For robustness, we re-estimate all relevant specifications using several alternative carbon-emissions measures, including overall emissions, as the dependent variable (reported in Online Appendix B). The results are qualitatively similar to those reported in the main text.

3.2.5. *Borrower climate exposure and realized emissions*

We use two measures to capture borrowers' expected exposure to climate regulation and realized emissions. First, borrower climate-change exposure is measured as the relative frequency of climate change–related bigrams in firms' earnings conference-call transcripts, following Sautner et al. (2023). We scale this variable by 1,000. We then define high-exposure (low-exposure) borrowers as those with climate-change exposure at or above (below) the median.

To measure actual emissions, we construct sector-level polluter indicators based on 2-digit NAICS codes and cross-industry emission intensity patterns, following Crosignani et al. (2025). An *extreme polluter* is defined as one if the borrower is in the Utilities sector (NAICS 22), as this sector has the highest emissions, zero otherwise. *High polluter* equals one for Mining/Oil/Gas (NAICS 21), Transportation (NAICS 48–49), or Agriculture/Forestry (NAICS 11), zero otherwise; *Medium-high polluter* equals one for chemicals, petroleum, or paper (NAICS 32), zero otherwise; *Medium polluter* equals one for food, textiles, metals, machinery (NAICS 33), zero otherwise; and *Low polluter* equals one for information and finance (NAICS 51–52), zero otherwise. All remaining sectors are classified as "Other".

3.2.6. *Country-level biodiversity score*

The Biodiversity & Habitat (BDH) Score measures a country's performance in protecting terrestrial and marine ecosystems, based on the 2024 Environmental Performance Index (EPI) developed by Yale and CIESIN. Higher BDH scores reflect stronger national biodiversity protection efforts. We compute annual country-level BDH scores from 2002 to 2022 following EPI's reweighting procedure. Details of the score construction are provided in Appendix A5.

3.2.7 *Other control variables*

Deal-level controls

We include standard loan contract features: *Deal amount* (total facility size in US dollars), *Maturity* (loan duration in months), and a *Secured loan* indicator (equals one if the loan is secured, and zero otherwise). *Lender avg. share* is the tranche-amount-weighted average stake across all tranches within the deal, following the methodology of Blickle et al. (2022). *Prior relationship w/ lender* is an indicator equal to one if the borrower and lender have engaged in at least one prior loan transaction observed in the dataset, and zero if the current loan is the first recorded transaction between the borrower–lender pair.

Borrower-level controls

We include borrower-level controls to account for firm-specific heterogeneity in credit risk and financial flexibility. *Firm size* $_{Borrower}$, measured as the natural logarithm of total assets, captures scale economies in financing and emissions management. Larger firms may face lower climate-related risk premia due to better disclosure practices and greater adaptability to transition risks (Delis et al., 2024). *Profitability* $_{Borrower}$, defined as EBIT scaled by total assets, serves as a proxy for internal debt-servicing capacity. *Leverage* $_{Borrower}$, calculated as total debt over total assets, controls for financial constraints that can amplify firms' exposure to carbon transition risks (Francis et al., 2022). These variables are standard in syndicated loan pricing models and help mitigate omitted variable bias in our estimations (Chava, 2014). To capture institutional variation in climate regulation, we include an indicator variable, *EU ETS* $_{Borrower}$, for whether the borrower is headquartered in a country subject to an Emissions Trading Scheme (ETS), consistent with Ehlers et al. (2022), who document the impact of carbon markets on loan pricing efficiency.

Lender-level controls

Larger and more profitable banks may be better equipped to internalize climate risks and allocate capital accordingly (Berger et al., 2024; De Haas and Popov, 2023). To account for lender heterogeneity in risk pricing, we control for *Size* $_{Lender}$ (log of total assets), *Profitability* $_{Lender}$ (EBIT scaled by total sales), and *Leverage* $_{Lender}$ (total debt over total assets), all obtained from Compustat Global. To capture lender's institutional variation in climate regulation, we also include *EU ETS*$_{Lender}$, an indicator for whether the lender is headquartered in a country subject to the EU Emissions Trading Scheme. These variables capture pricing differences related to scale, risk horizon, and collateralization (Giannetti and Laeven, 2012; Santos and Winton, 2008).

Country-level controls

We control for a set of borrower-country characteristics. *Same legal origin* is a dummy variable equal to one if both the borrower and lender countries share the same legal origin (either civil law or common law), and zero otherwise. *GDP growth* is measured as the annual percentage change in real GDP per capita, capturing year-over-year economic growth at the country level. *Total emissions* represents the country's total anthropogenic greenhouse gas emissions from S&P Trucost, expressed in CO_2 equivalent. *Climate readiness* reflects a country's ability to leverage private and public sector investment to implement adaptive actions in response to climate change. All continuous variables are winsorized at the 1st and 99th percentiles. Detailed variable definitions and sources are provided in Appendix A2.

3.3 Empirical Methodology

3.3.1 *Stacked difference-in-difference regression*

Countries introduce carbon taxes at different times and for various reasons, including differences in economic structure, political priorities, or environmental policy objectives. These differences can create heterogeneous responses. For carbon intensity, policy timing and country characteristics (e.g., industrial mix, abatement opportunities) may drive sharp changes at the time of adoption ($t = 0$) with effects that persist. For loan costs, lenders may adjust earlier or later, leading to pre-trends or delayed responses.

Recent econometric work (e.g., Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021) demonstrates that the TWFE-DID model can yield biased estimates when treatment timing is staggered and effects are heterogeneous. Evidence from finance (e.g., Karpoff and Wittry, 2018; Baker et al., 2022) confirms that these biases are relevant in research settings in finance that rely on staggered treatment timing. Because our setting involves the staggered adoption of carbon taxes across countries and potential heterogeneity in treatment effects, we employ a stacked regression difference-in-differences (DID) framework, comparable to Gormley and Matsa (2011) and Cengiz et al. (2019), to identify the impact of carbon tax policy on foreign lending. This approach enables comparisons between treated borrower firms subject to a carbon tax and "control" firms with no carbon tax. The stacked DID design improves identification by: (i) comparing similar treated and control groups around each policy event; (ii) avoiding already-treated countries as controls; and (iii) producing clean event-time coefficients that are not averages of very different country experiences.

We estimate the average treatment effect of stacked DID regression using the following specification:

$$Y_{borrower,cohort,t} = \alpha + +\beta_1 PostCT_{borrower,t} + \gamma X_{\mathrm{deal},t} + \delta Z_{lender,borrower,t-1}$$
$$+\mu_{1_{cohort,borrower}} + \mu_{2_{cohort,lender}} + \mu_{3_{cohort,t}} + \varepsilon_{borrower,cohort,t}. \quad \ldots (1)$$

The dependent variable Y is measured using two alternative outcome variables, depending on the specifications. Y is *Log(Carbon intensity)*, defined as the natural logarithm of Scope 1 CO_2 emissions (metric tons per USD 1 million of borrower firm revenue) in year t, assigned to the deal arranged by the lead arranger(*lender*). Or, Y is *Log (Cost of loan)*, defined as the natural logarithm of the all-in-spread-drawn (in basis points), charged by the lead arranger to the borrower for the deal in year *t*. $PostCT_{Borrower,\,t}$ *is* an indicator that equals one if the borrower country has a carbon tax in place in year *t,* and zero otherwise. X represents a vector of deal characteristics at year *t*. Z represents a vector of continuous lead arranger, borrower, and borrower's country characteristics at year *t-1*. $\mu1$-$\mu3$ represent cohort-borrower, cohort-lender, and cohort-time fixed effects, respectively.

The stacked regression procedure is implemented as follows. We define a *cohort* as the set of treated and control borrower firms aligned to a common policy-adoption year. We construct three treatment cohorts around major carbon pricing initiatives: Cohort 2005 (the launch of the EU ETS), Cohort 2008 (the introduction of the New Zealand ETS and Switzerland's carbon tax), and Cohort 2012 (widespread adoption of carbon taxes, including in Japan). Appendix Table A4.1 summarizes the cohort years, cohort composition, and the rationale for their selection.

Treatment cohorts are defined by a country's first adoption of either an ETS or a carbon tax.[4] For each adoption year, we construct a ±2-year event window and compare treated countries to a propensity-score–matched set of control countries that have not yet adopted either policy; countries that adopted earlier are excluded from the control pool. In the stacked design, a country may serve as a control in earlier cohorts and later enter as treated in its own cohort, but it is never used as a control after adoption. Matching is based on pre-treatment borrower-country characteristics, including GDP growth and total greenhouse gas emissions. We then stack cohorts and estimate effects in common event time, which reduces negative weighting and treatment-contamination concerns in staggered TWFE and improves the interpretability of dynamic effects.

[4] Following Laeven and Popov (2023), we incorporate EU ETS adoption timing alongside carbon taxes in the staggered DID framework to define treatment cohorts.

Details are provided in Online Appendix B.1. The sample spans 2002–2022 and is unbalanced due to differences in event timing across cohorts. To ensure comparability, we require both treated and control firms to have at least one pre-event and one post-event observation. As a robustness check, we also estimate a pooled stacked design without matching.

We employ a rich fixed-effects structure to account for unobserved heterogeneity and common shocks. Cohort × lender fixed effects control for time-invariant lead-arranger characteristics (e.g., internal ESG and risk policies). Cohort × borrower fixed effects control for time-invariant borrower characteristics (e.g., baseline emissions intensity and industry technology). Cohort × year fixed effects absorb cohort-specific global shocks and time trends in climate policy and financial conditions. Standard errors are clustered at the borrower-country level to account for within-country correlation in regulation and lending outcomes suggested by Petersen (2008) for loan-level panel data.[5]

3.3.2 *Dynamic difference-in-difference regression*

In addition, we implement a dynamic version of regression (1) to estimate the year-by-year treatment effects in the years preceding and following treatment. Five dummy variables identify pre-treatment and post-treatment years for borrower firms in the cohort, where $t = 0$ represents the year of carbon tax implementation, around which we build the treatment-control cohort panel. The omitted year is $t = -1$ (the year prior to treatment). The regression coefficients capture the change in the outcome variable for the treated group between years $t+2$ and $t-2$, compared to the control group in the cohort. This specification allows us to test for pre-treatment trends (via the $t-2$ coefficient) and trace out the dynamic treatment effects over time.

[5] This setup follows recent climate-finance and monetary-policy studies (e.g., Dikau and Volz, 2021) and helps limit bias from unobserved institutional or country-level factors.

3.4 Summary Statistics

Panel A of Table 1 provides descriptive statistics for all relevant variables in our empirical analysis. The average (median) carbon intensity of approximately 425 (22) metric tons of CO_2 per $1 million USD in revenues is higher than in other studies of carbon intensity, such as the 192 (15) reported by Bolton and Kacperczyk (2021) and 166 (15) from Aswani et al. (2023). Our higher values are due to our sample period which includes earlier periods in the 2000's when emissions intensity was higher, as well as the generous winsorization (at 2.5% and 97.5%) of Bolton and Kacperczyk (2021) and Aswani et al. (2023), which reduces their realized carbon intensity values (see Aswani et al., 2023, for a detailed discussion of optimal winsorization practices for carbon intensity data). Likewise, our average loan cost, measured by spreads, stands at approximately 1.94%, which is close to the 2.25% reported by Erten and Ongena (2024) for a similar sample. The high proportion of foreign loans (25.1%) indicates substantial international exposure among syndicated lenders, consistent with the globalized nature of syndicated lending markets documented by Laeven and Popov (2023) and Benincasa (2021).

Table 1 Panel B presents the correlation matrix, revealing several significant relationships among the variables of interest. Carbon intensity negatively and significantly correlates with borrower (-0.041) carbon tax indicators, suggesting firms in jurisdictions with carbon taxes tend to have lower carbon footprints. Moreover, the significant positive correlation (0.461) between secured loans and loan costs aligns with the risk-based pricing model suggested by Fard et al. (2020), reflecting lenders' concerns about potential defaults and recoveries.

Table 2 presents the top lender and borrower countries by share of total deal amount. The sample is dominated by U.S. institutions, which account for 73.56% of loan observations, demonstrating the central role of U.S. arrangers in global syndicated lending. The next largest lender domiciles are the United Kingdom (6.00%), Germany (4.33%), Switzerland (3.00%), France (2.81%), Canada (2.66%), Japan (2.54%), and the Netherlands (2.15%), with all remaining countries each contributing less than 1%. Borrowing is somewhat less concentrated but still U.S.-centric, with U.S. borrowers representing 69.78% of total deal volume, followed by the United Kingdom (5.72%), France (2.86%), Canada (2.67%), and Germany (2.43%). Overall, the distribution indicates that the syndicated loan sample is heavily weighted toward advanced-economy participants, reflecting the depth and global integration of North American and Western European banking networks during the 2002–2022 period. To ensure that this concentration does not influence our main results, Online Appendix B reports robustness tests that exclude U.S. lenders and borrowers, and separately examine firms subject to the European Union Emissions Trading System (EU ETS).

4. Effects of Carbon Tax on Foreign Lending

4.1 Stacked-DID Results

Table 3 presents the matched stacked DID results for the full and foreign loan samples. The outcome variables are *Log (Carbon intensity)*, measured as the natural logarithm of Scope 1 CO_2 emissions expressed in metric tons per USD 1 million of borrower firm revenue, and *Log (Cost of loan)*, measured as the natural logarithm of the all-in-spread-drawn, expressed in basis points, charged by the lender to the borrower firm for a given deal at year *t*. The coefficients on $PostCT_{Borrower}$ are negative in Panel A, Columns (1)-(3), for carbon intensity, implying an approximately 11% to 13% decline in carbon intensity following carbon-tax adoption.[6] The estimates are highly significant in two columns (1) and (2), and marginally significant in the full

[6] In Table 3, Panel A, Column (3), $e^{(-0.119)} - 1 \approx 0.112$, implies a 11.2% reduction in carbon intensity. The median value of carbon intensity from Table 1, Panel A, is 22.04 metric tons of CO_2 per \$ 1 million in revenue. The reduction is $22.04 \times 0.112 \approx 2.47$ metric tons CO_2 per USD 1M revenue.

specification (Column (3)). In Panel B, the corresponding decline for foreign loans is larger in magnitude, ranging from approximately 14% to 21%. The reduction is also economically meaningful, corresponding to a decline of 3.1 to 4.7 metric tons of CO_2 per $1 million in revenue, relative to the median. The estimates are marginally significant for our baseline model (Column (1)) and are highly significant when we include lender or borrower-country controls (Columns (2) and (3)).

In contrast, when we consider loan costs in Table 3 Panel A, $PostCT_{Borrower}$ is statistically insignificant in Columns (4) - (6). In Column (6), the estimates imply that loan costs increase by only about 2.3 basis points (about 1.5%), and this estimate is statistically insignificant. While carbon taxes lead to clear shifts in portfolio composition, the evidence in Columns (4) - (6) indicates that their direct effect on loan pricing is limited. In the foreign-loan sample, we find no detectable change in loan pricing either. By comparison, in Table 3 Panel A Column (6), the coefficient of $EU\ ETS_{\ Borrower}$ corresponds to a sizable 30 basis-point increase in loan spreads, equivalent to a 19% jump from the median value, suggesting that cap-and-trade systems influence lending primarily through risk repricing rather than portfolio adjustments.[7]

In syndicated lending, delegated-monitoring theory predicts that lead arrangers retain larger shares to mitigate moral hazard for opaque borrowers (Holmström, 1979; Holmström and Tirole, 1997; Sufi, 2007), yet Blickle et al. (2022) show that arrangers frequently sell down their shares shortly after origination - for over half of term loans and 70% of institutional tranches - without underperformance relative to loans they retain. Consistent with this, our evidence indicates that carbon-tax adoption reshapes syndicated lending primarily through portfolio rebalancing and

[7] In Column (6), $e^{(0.177)} - 1 \approx .194$, implies a 19.4% increase in cost of loan. The median value of the cost of loan from Table 1 Panel A is 156.3 bps. The increase is $156.3 \times (0.194) \approx 30.32$ bps.

risk transfer. Loan carbon intensity declines, while average loan-cost effects are limited; yet, lenders retain larger shares in higher–carbon–intensity and higher-cost deals, as reflected in the positive coefficient on *lender avg. share*.

4.2 Dynamic Effects and Parallel Trend Assumption

We next implement a matched-sample stacked DID regression as discussed in Section 3.3.2 to estimate dynamic treatment effects around the introduction of a borrower-country carbon tax. Five event-time dummies identify the years from *t-2* to *t+2*, with *t = 0* denoting the year of carbon tax implementation and *t-1* (the year prior) serving as the reference period. Figures 1a and 1c plot the dynamic coefficients for the two outcome variables for all loans: *log (Carbon intensity)* and *log (Cost of loan)*, respectively.

The results are broadly consistent with our findings in Table 3. Figure 1a illustrates a steep decline in borrower carbon intensity at the year of implementation (t = 0), which persists over the subsequent two years. By contrast, Figure 1c shows an initial decline in loan costs in the implementation year of a carbon tax. However, this drop is reversed in subsequent years and stabilizes at a level similar to the pre-tax position. Figure 1b and Figure 1d display similar trends using the subsamples of foreign loans only.

Table 4 reports the corresponding regression estimates. In Panel A, Columns (1) to (3), the coefficient on $PostCT_{Borrower,t}$ is negative (–0.115 to –0.129), indicating that borrower carbon intensity declines by about 11% to 12% at the time of policy introduction. Significance varies across models. Coefficients in later years (*t+1* and *t+2*) are negative but statistically insignificant, suggesting that the largest adjustment occurs immediately at implementation**,** with limited evidence of persistence beyond the adoption year. For foreign loans (Panel B), the decline in carbon intensity in the implementation year is significant and more pronounced (–0.177 to –0.211), corresponding to about 16% to 19% decline, indicating a sharper immediate adjustment in cross-border lending. The decline in carbon intensity is largely insignificant in *t+1* and *t+2* years. In Column (6) of the foreign-loan subsample, loan costs increase in *t+2* (two years after adoption), whereas we do not observe a comparable rise for the full sample (Panel A).

An identifying assumption in our DID framework is the absence of differential pre-trends between treated and control borrowers. In other words, prior to the policy adoption, lender portfolios should exhibit similar carbon intensity and no systematic difference in loan costs between countries that later implement a carbon tax and those that do not. If this assumption is violated, the estimates would capture pre-existing differences rather than the causal impact of the carbon tax.

For borrower carbon intensity, the insignificant coefficient on $PostCT_{Borrower,\ t-2}$ in Columns (1)-(3) of both panels validates the parallel trends assumption, by indicating no systematic differences between treated and control firms two years before carbon tax adoption. For loan costs, the evidence is less supportive. In both panels, $PostCT_{Borrower,\ t-2}$ is positive and significant only in Column (6), the specification with lender and country controls, indicating that spreads begin to rise before implementation. This pattern is consistent with anticipatory repricing, where lenders adjust terms in advance of the formal adoption year, possibly in response to expectations of imminent implementation. Accordingly, we interpret the foreign-loan pricing dynamics more cautiously, while the carbon-intensity dynamics provide cleaner support for a causal effect.

4.3 Alternative Specifications and Robustness Tests of Baseline Models

Online Appendix B reports several robustness checks and alternative specifications for the baseline results in Table 3. We begin with alternative dependent variables and simplified benchmark models, followed by pooled specifications, alternative fixed effects structures, and tests for sample composition concerns.

Table OAB.I replaces carbon intensity as the dependent variable with raw (i.e., unlogged) total emissions, log total emissions, and emissions scaled by total assets, reflecting the measurement debate in Bolton and Kacperczyk (2021) and Aswani et al. (2023). The results closely track those from the baseline specification and generally strengthen when using total emissions. Because total emissions measures (raw or unlogged) place greater weight on larger firms - consistent with a stronger post–carbon tax decline in emissions for such borrowers - we retain carbon intensity as the primary dependent variable in the main text for comparability and interpretability. Untabulated tests confirm that other analyses (where feasible) yield comparable findings when total emissions are used instead.

We focus on matched stacked DID estimates in our main text because these specifications are most effective in addressing comparability across taxed and non-taxed borrowing firms. However, the matched stacked DID framework addresses comparability concerns at the cost of reduced sample size and statistical power. Table OAB. II uses a less restrictive pooled (i.e., non-matched) sample to estimate the staggered DID models. This specification allows for a larger and more heterogeneous sample. The results increase the strength (both magnitude and significance) of our main findings (i.e., a more pronounced decline in carbon intensity, especially for foreign loans, following a carbon tax). Therefore, our matched stacked DID approach offers a conservative estimate of the association between carbon taxes and the emissions intensity of lending.

We continue to expand our sample with a more simplified TWFE model, excluding the stacked cohort procedure. We are cautious in our interpretations from these models, as the potential for heterogeneous treatment effects makes inferences unclear. However, these models are useful for comparison with the existing literature, which often relies on two-way or multidimensional fixed effects rather than our stacked DID approach (e.g., Laeven and Popov, 2023). In Table OAB. III, we continue to observe significant negative relationships between carbon taxes and carbon intensity, but now only for foreign loans (Panel C). The interaction term approach in Panel C, $PostCT_{Borrower} \times$ *Foreign loan*, captures the differential effect of a borrower-country carbon tax on carbon intensity and loan costs for foreign loans relative to domestic loans, consistent with related approaches in the literature.[8] Overall, Table OAB.III shows that the main patterns remain directionally consistent but are less precisely estimated and continue to indicate that cross-border lending is associated with a larger post-carbon tax decline in borrower carbon intensity.

Differences in fixed effects structures are a major source of variation in methodology across empirical approaches and can, in turn, affect the estimated results. Table OAB.IV continues the stacked DID models, but with alternative fixed effects structures, such as dropping lender fixed effects or including lender country fixed effects. The findings suggest that our baseline estimates are robust to less strict fixed effects structures. We observe comparable coefficient magnitudes, as well as stronger statistical significance.

Table OAB.V addresses concerns that our sample is dominated by US-based firms. Panel A drops US-based borrowers, and Panel B drops US-based lenders. Despite the large drops in sample size, both models continue to yield significantly negative coefficient estimates for the association between $PostCT_{Borrower}$ and carbon intensity. Both models also tend to yield larger coefficient estimates, reflecting the reasonable conclusion that non-US firms (both borrowers and lenders), mostly now drawn from Europe, display even stronger associations between carbon taxes

[8] In the stacked DID models, matching eliminates within-cohort variation in lender type, meaning that the foreign-loan indicator does not change with the carbon-tax implementation. As a result, there is no remaining variation to support an interaction term involving foreign lending.

and carbon intensity, compared to our baseline models. Panel C explores the other side of this aspect by dropping borrowers subject to the EU ETS (and dropping the control variable for *EU ETS* $_{Lender}$). Interestingly, this table yields coefficient estimates that are negative, highly significant, and larger in magnitude than those in our baseline models. This confirms that our results are not confined to EU borrowers or the impact of the EU ETS.

5. Variation Based on Borrowers' Climate Exposure, Pollution, and Environmental Policy

Thus far, our analysis shows that carbon emissions decline following the introduction of a carbon tax, while changes in loan pricing remain limited. Consistent with Laeven and Popov (2023) and Benincasa et al. (2022), we find that these effects are particularly pronounced for a subset of foreign loans, though they also appear in the full sample. However, the domestic–foreign distinction captures only one dimension of heterogeneity across borrowers. Prior research indicates that lenders' responses to climate policy may also vary with borrowers' exposure to climate regulation (Sautner et al., 2023; Delis et al., 2024), emissions intensity embedded in industry activities (Chava, 2014; Crosignani et al., 2024), and the broader national policy environment in which borrowers operate (Houston et al., 2012; Benincasa, 2021). In this section, we examine each of these dimensions in turn to assess which borrower characteristics account for differences in lending outcomes following the implementation of carbon taxes.

5.1 Borrower's Climate Change Exposure

We begin by examining whether borrowers' exposure to climate regulation shapes lending responses to carbon taxes. We measure climate change regulatory risk using *climate change exposure*, a textual measure developed by Sautner et al. (2023), defined as the relative frequency of climate change–related bigrams in firms' earnings conference call transcripts. This measure captures how prominently climate-related regulatory issues feature in managerial discourse. To assess heterogeneity across borrowers, we split the sample at the median of *climate change exposure*.

Table 5 reports the results. Columns (1)-(3) present estimates for loan carbon intensity, while Columns (4)-(6) present estimates for loan pricing. Panels A and B report results for all loans and foreign loans, respectively, for borrowers with at- or above-median climate change (*high-exposure*) category. In the all loans sample (Panel A), $PostCT_{Borrower}$ is negative and statistically significant in Columns (1)-(3), indicating a reduction in carbon intensity following the adoption of a carbon tax. For foreign loans (Panel B), statistical significance is sensitive to model specification, but the estimated decline becomes larger in magnitude and statistically significant once additional controls are included**.** Across both panels, we find no systematic evidence of loan repricing, consistent with earlier results suggesting that post–carbon tax adjustments operate primarily through changes in carbon intensity rather than through spreads.

A different pattern emerges when we turn to borrowers with below-median climate change (*low-exposure*) category. Panels C and D of Table 5 show that, in the all loans sample, the decline in carbon intensity following a carbon tax remains negative and statistically significant, with magnitudes that are somewhat smaller than for high-exposure borrowers. For foreign loans, however, borrowers with low exposure exhibit the largest and most pronounced reductions in carbon intensity after carbon tax adoption (Panel D), although statistical significance is sensitive to specification**.** Taken together, these results suggest that when climate change exposure is high, emissions decline for both all loans and foreign loans. When exposure is low, by contrast, we observe a pattern consistent with foreign lenders shifting toward cleaner borrowers within the low-exposure group, producing sharper reductions in emissions at the lower end of the exposure distribution.

While informative, climate change exposure primarily reflects the salience of climate-related narratives in corporate communications, rather than the actual emissions or regulatory liabilities. As such, it may diverge from measures based on firms' actual production technologies or industry characteristics. To assess the robustness of these patterns, we next turn to alternative borrower-level measures based on industry pollution intensity.

5.2 Borrower's Pollution Level

We next examine heterogeneity in lending responses using an alternative borrower characteristic that is closer to realized emissions: industry-level pollution intensity. Rather than relying on climate-related narratives in corporate communications, this approach captures differences in borrowers' production technologies and business activities. Specifically, we assign each borrower an industry pollution category based on its primary industry classification, following the methodology of Crosignani et al. (2024). Industries are ranked by pollution intensity, allowing us to estimate a category-based specification that traces how lending outcomes vary across increasingly emissions-intensive sectors. In Section 3.2.5, we present the classification of borrowers into extreme polluters, high polluters, medium-high polluters, medium polluters, low polluters, and others (an omitted category in the regression).

Table 6 reports the results. In the all-loans sample (Panel A), carbon intensity declines following the introduction of a carbon tax, with the largest and most statistically significant effects concentrated among borrowers in the most highly polluting industries, *extreme polluters*. For borrowers in cleaner industries, the estimated responses are smaller and insignificant. These findings reinforce the conclusion that carbon taxes induce lenders to reduce exposure primarily to the highest emitters. Consistent with this pattern, loan costs also fall most sharply for extreme polluters.

Once again, the pattern differs for foreign lending. In Panel B of Table 6, reductions in carbon intensity remain evident but are no longer concentrated among the most polluting industries. Instead, the strongest response appears among medium-high polluters. This shift aligns with the evidence from Table 5. Moreover, though carbon intensity declines most strongly for medium- to high-polluters, loan costs fall most for extreme polluters, indicating that foreign lenders' adjustments operate through both borrower composition (carbon intensity) and pricing/economic exposure (loan costs), but not necessarily in the same pollution segment. Together, these results point to partial segmentation between all loans and the foreign loans sample in the transmission of carbon taxes.

This distinction complements Laeven and Popov (2023), which show that when a country introduces a carbon tax, banks domiciled in that country reduce fossil lending at home but increase fossil lending abroad. Our analysis speaks to a different (but complementary) margin**.** With our more granular pollution classification across a broad set of industries, we show that post-carbon tax decarbonization and pricing adjustments vary systematically across pollution categories and differ between the all-loans and foreign loans samples. Taken together, carbon taxes can reshape credit not only through the geographic reallocation of carbon-intensive lending but also through changes in the pollution-segment composition and pricing of the loan portfolio.

As an additional robustness check, we estimate quantile regressions that allow the carbon-tax effect to vary with borrowers' prior-year carbon-intensity quintile. Specifically, Table OAB.VI (Online Appendix B) sorts borrowers into five quintiles based on prior-year carbon intensity (Q5 is the highest quintile; Q1 is the omitted category) and interacts these quintile indicators with the post-carbon tax treatment. The results corroborate the categorical findings. Reductions in loan carbon intensity are concentrated in the upper tail of the emissions distribution, consistent with evidence from Crosignani et al. (2025), which shows that a small set of "super-emitters" drives many climate-related financial outcomes. When restricting the sample to foreign loans, the strongest effects shift downward in the distribution, with the largest response observed in the fourth quintile rather than among the most extreme emitters. This pattern aligns closely with the results in Tables 5 and 6, further supporting the presence of differentiated adjustment mechanisms among foreign lenders.

5.3 Borrower's Country-level Environmental Policy

As the final measure of variations across borrowers based on the environmental regulatory landscape, we shift our focus to national-level environmental policy. We examine whether more stringent environmental regulation, distinct from explicit carbon emissions policies, interacts with carbon taxation in shaping cross-border lending. We measure environmental regulation strictness at the country level to avoid the issues that may arise when climate policy applies differently across borrowers. To capture country-level environmental policy, we use the *biodiversity score*, defined as the borrower's country-year level Biodiversity & Habitat (BDH) score from the Environmental Performance Index (EPI), which measures national efforts to protect terrestrial and marine ecosystems. A higher score indicates greater protection for biodiversity.

The results in Table 7 show that biodiversity scores are unrelated to carbon intensity, confirming the distinctiveness of biodiversity outcomes relative to carbon emissions. However, we also observe positive and statistically significant coefficient estimates on the interaction between biodiversity score and carbon tax in the sample of all loans (Panel A). This implies that the post-carbon tax decline in loan carbon intensity is weaker in countries with stronger biodiversity protection. Equivalently, carbon-intensity reductions are concentrated in countries with more lenient environmental regulation. In Panel B (foreign loans), the interaction terms are generally positive but only marginally significant in Column (3), indicating no systematic differential response in foreign lending along the biodiversity policy dimension.

This is consistent with our borrower-level evidence in Table 6: the sharpest post-carbon tax reductions in loan carbon intensity are driven by high-emitting borrowers and environments where there is more scope to reduce exposure, whereas the effects are weaker among cleaner borrowers. The positive interaction in Panel A is consistent with a weaker post-carbon tax decline in carbon intensity in high-biodiversity-protection countries, which aligns with the broader theme that the strongest adjustments occur in countries with higher baseline carbon intensity. Finally, Table 7 provides little evidence that biodiversity policy amplifies loan-cost responses to carbon taxes.

These findings add an interesting aspect beyond our carbon-tax–only analysis. The biodiversity interaction demonstrates that the carbon tax effect on lending carbon intensity depends on the broader environmental policy environment. In practice, carbon and biodiversity regulations often arrive as a package, and the interaction term captures how lenders perceive the tradeoff between multiple environmental mandates. Overall, the results from Table 7 reinforce that the post-carbon tax adjustment operates primarily through changes in the carbon intensity of lending rather than systematic repricing.

6. Credit Reallocations between Domestic and Cross-border Lending

6.1 Cross-border Lending

In this section, we investigate how the implementation of a carbon tax affects the allocation of cross-border loans by syndicated lenders. As described in Section 3.2.2, each lender’s share is measured by first calculating each lead arranger's predicted loan exposure (Blickle et al., 2022; Appendix A1) and then aggregating these exposures to the lender–borrower country-year level. Foreign and domestic exposures are summed separately to construct the dependent variables: *foreign loan share* and *domestic loan sh*are, both measured in the year following the introduction of a carbon tax. Borrower-level controls are weighted by loan size, while lender- and country-level variables are preserved at their original values. This aggregation transforms loan transactions into portfolio allocations, allowing us to analyze how environmental policies shape the geography of syndicated lending.

Table 8 examines how borrower-country carbon taxes affect foreign lenders' portfolio allocation. The dependent variable is *foreign loan share*. Columns (1)-(3) provide evidence on short-term (i.e., year *t+1*, the first year after adoption) cross-border spillovers, while Columns (4)-(6) present results for the medium-term impact at time *t+3* (the average annual foreign loan share over the three years after adoption). $PostCT_{Borrower}$ equals one from the year a carbon tax is introduced in the borrower's country onward; $PostCT_{Lender}$ equals one from the year a carbon tax is introduced in the lender's country onward; and $PostCT_{Borrower\ \&\ Lender}$ equals one if, in the year the borrower's country introduces a carbon tax, the lender's country already has an active carbon tax.

The lack of significance for estimates in year *t+1* suggests that cross-border loan reallocations are not immediate. However, the significant negative estimate on $PostCT_{Borrower}$ in the medium term implies that a carbon tax in the borrower's jurisdiction is associated with a drop in foreign lenders' shares over the subsequent three years. The positive and significant coefficient on $PostCT_{Lender}$ in Column (5) suggests that lenders domiciled in carbon-tax countries tend to hold higher foreign loan shares in the medium term. The positive and significant coefficient on

$PostCT_{Borrower\ \&\ Lender}$ in Column (6) indicates the medium-term decline in loan share is attenuated when lenders are domiciled in countries that already have an active carbon tax at the time the borrower adopts one.

6.2 Domestic Lending

Table 9 Panel A examines the effect of borrower-country carbon taxation on the domestic portfolios of syndicated lead arrangers. In Columns (1)-(3), the negative and statistically significant coefficients on $PostCT_{Borrower}$ indicate that carbon intensity declines following the introduction of a carbon tax for domestic loans. $PostCT_{Borrower}$ is positive and significant in Column (5), suggesting significantly higher loan costs when we control for lender characteristics.[9] This reduction may reflect lower carbon intensity among domestic borrowers post-tax and/or competitive adjustments by domestic lenders.

Table 9, Panel B, shifts the focus to the participation of lenders over time in the domestic loan market, using *domestic loan share* measured at *t+1* and *t+3*. In Column (1), we find that the domestic loan share increases significantly after the adoption of a carbon tax in the borrower's country in year *t+1*, as shown by the positive and significant coefficient on $PostCT_{Borrower}$. This increased participation by domestic lenders remains strong and significant at the three-year horizon (Column (2)). Therefore, carbon taxes provide domestic lenders with a relative advantage, enabling them to increase and maintain their market share.

The overall findings from Tables 8 and 9 indicate that carbon taxes are followed by meaningful credit reallocation over time. This behavior aligns with prior evidence from Popov and

[9] One caveat is that Dealscan data captures only domestic loan portfolios of syndicated lead arrangers. We do not observe the effect on smaller domestic lenders that do not participate in syndicated lending. As such, the observed decrease in carbon intensity may signal a perverse spillover, where smaller, less-visible domestic lenders absorb more carbon-intensive exposures, thereby increasing the overall risk profile of their loan portfolios.

Udell (2012), Avdjiev et al. (2019), Erten and Ongena (2024), and especially Laeven and Popov (2023), who document banks' tendencies to adjust lending geographically in response to differential regulations. Our results extend the existing literature by demonstrating that foreign lenders retreat following the adoption of a carbon tax (Table 8), while domestic lenders simultaneously lower their portfolio carbon intensity and increase their domestic loan share (Table 9).

7. Conclusion

This paper examines how carbon taxation alters the allocation and pricing of syndicated credit across borders. Using a stacked difference-in-differences approach from 2002 to 2022, we find that the introduction of carbon taxes reduces the carbon intensity of foreign loan portfolios by about one-fifth, primarily due to the reallocation of lending rather than higher spreads. In contrast, the European Union Emissions Trading System (ETS) is associated with an average increase of about 30 basis points in loan costs, indicating that taxes and cap-and-trade regimes affect financial intermediation through distinct channels, the former by shifting portfolios, and the latter by repricing risk.

The decline in loan carbon intensity following the adoption of a carbon tax is not uniform across borrowers but depends systematically on exposure, emissions characteristics, and national policy environments, while loan pricing remains largely unchanged. Using textual measures of climate change exposure, industry-level pollution rankings, and borrower-level emissions quantiles, we find that the all-loans sample reduces exposure most strongly to the highest emitters. Foreign lenders, by contrast, adjust along a different margin: emissions reductions are concentrated among borrowers with lower climate exposure or medium-high pollution levels, rather than among extreme polluters. This pattern is consistent across narrative-based, industry-based, and emissions-based measures, suggesting partial segmentation between domestic and foreign credit markets in how carbon taxes transmit through lending portfolios.

Extending the analysis to country-level environmental policy, we show that carbon taxes interact with broader ecological regulations in shaping lending outcomes. While biodiversity policy is mechanically unrelated to carbon intensity, the post–carbon tax decline in loan carbon intensity is weaker in countries with stronger biodiversity protection**.** This evidence aligns with the borrower-level results, indicating that the largest adjustments occur where high emitters remain prevalent, whereas lending to cleaner borrowers may expand in more stringently regulated environments. Taken together, these findings indicate that carbon taxes primarily operate through credit reallocation rather than repricing, and this reallocation reflects both borrower-level emissions profiles and the broader regulatory context in which firms operate.

Overall, carbon taxes induce a gradual reallocation of syndicated credit between domestic and cross-border lending. Foreign lenders retrench from taxed jurisdictions, cutting their cross-border lending shares within three years. In parallel, domestic lenders expand and sustain their market share following carbon tax adoption, while simultaneously lowering the carbon intensity of their domestic portfolios. When both lender and borrower countries adopt carbon taxes, this divergence disappears, consistent with international policy coordination lowering incentives for regulatory arbitrage. These results suggest that uncoordinated carbon taxation can achieve local decarbonization; however, it also creates scope for cross-border shifts in exposure that can limit the policy's global reach. Taken together, these results indicate that carbon taxation reshapes the geography of lending through portfolio reallocation consistent with regulatory arbitrage, while also allowing domestic lenders to consolidate their position in home markets rather than exit high-carbon lending altogether.

This study also contributes methodologically by tracing post-origination loan exposures, showing how lead arrangers adjust their holdings in secondary markets after a policy shock. The evidence indicates that arrangers manage transition risk primarily by rebalancing exposures and through better screening rather than by raising borrowing costs. This finding refines existing theories of delegated monitoring, showing that informational advantages can substitute for balance-sheet commitment in managing climate-related risks. Yet, lead arrangers retain larger shares in higher-carbon-intensity and higher-cost deals, indicating a greater "skin in the game" precisely when loans appear riskier, which is also consistent with informed-lender monitoring and screening in the face of heightened transition risk.

Overall, the evidence indicates that carbon taxation reshapes financial intermediation primarily through portfolio choice, with the location and composition of these adjustments depending critically on borrower characteristics and the alignment of regulatory regimes across countries. In the absence of coordination, lenders can partially offset local decarbonization by shifting their exposures across borders or toward different segments of the emissions distribution, limiting the global reach of the policy. By contrast, overlapping carbon taxes across lender and borrower jurisdictions dampen incentives for regulatory arbitrage and lead to more uniform adjustments in lending portfolios. These findings suggest that carbon taxation can discipline the carbon content of credit without raising borrowing costs, but its effectiveness hinges on policy consistency and on how financial intermediaries reorganize risk across markets in response to uneven regulatory landscapes.

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Appendix A1: Sample Construction

Our analysis begins with 2,808,309 loan-level observations from the DealScan database. We apply sample restrictions to focus on primary syndicated loan deals with observable lender-borrower relationships. We exclude Term Loan B facilities and non-syndicated loans, and limit the sample to deals from the period 2002 to 2022, resulting in a sample of 1,698,455 observations.

The lead arranger's holding share is a key variable in constructing the measures in our analysis. While DealScan reports each lender's share in syndicated deals from 2002, approximately 75% of these observations are missing. For the non-missing cases, we exclude deals where the total lender shares sum to less than 98% or more than 102%, to account for data entry errors. To focus on banks, we restrict the sample to institutions with "Bank" in their reported institution type, following Blickle et al. (2022). Since our study focuses on lead arrangers, we retain only loans for which the 'lead_per_tranche' variable is non-missing, thereby reducing the number of observations from 1.6 million to 266,504 observations. We adopt the methodology of Blickle et al. (2022) to compute the average holding share of each arranger across all tranches and restrict the sample to one unique arranger per deal to avoid double-counting, yielding 152,021 observations.[10, 11] We then merge the loan data with holding share information to compute lenders' exposure to individual loans. Observations with missing predicted holdings are dropped. We verify that the attrition at this stage does not display systematic patterns by year, country, or industry.

We then link borrower-level financial data from Global Compustat using borrower GVKEYs provided by Chava (2014). It reduces the number of observations to 98,103. Lender financial data are merged using GVKEYs identified through Schwert's (2018) mapping procedure, supplemented by a fuzzy matching algorithm. This results in a matched lender–borrower sample of 54,141 syndicated loan observations with non-missing weighted spreads and maturities calculated at the deal level using tranche-level data.

[10] We identify 205,686 unique lead arrangers.
[11] Blickle et al. (2022) calculate holding share at the tranche level; we calculate the average holding of the lead arranger in a unique deal.

Because some borrower/lender controls and key outcome variables are missing, sample sizes differ across specifications. Regressions that require borrower carbon intensity (Scope 1 CO_2 emissions from Trucost) include 11,654 observations, while specifications that include loan cost from DealScan include 25,250 observations. This variation in sample size is in line with prior work using environmental and syndicated loan data (e.g., Delis et al., 2019; Kleimeier and Viehs, 2021) and reflects the still incomplete, though improving, coverage of firm-level environmental metrics.

The lower number of observations in the regression sample, relative to the descriptive statistics, reflects the cohort formation in the stacked DID specification and the use of fixed effects, which automatically drop singleton observations that do not contribute to identification. The construction of treatment cohorts and the resulting sample structure are described in Appendix A4.

Appendix A2: Variable Definitions

Variable	Definition	Source
Carbon variables		
Carbon intensity	Log (borrower firm's carbon intensity, Scope 1) measured as annual Scope 1 in metric tons of CO_2 per USD 1M revenue, measured at the deal-lender-year level	Trucost
$PostCT_{Borrower}$	An indicator equal to one from the year a borrower's country adopts a carbon tax onward, and zero otherwise	www.carbontax.org
$PostCT_{Lender}$	An indicator equal to one from the year a lender's country adopts a carbon tax onward, and zero otherwise	www.carbontax.org
Loan variables		
Cost of loan	Natural log of all in spread drawn in basis points at the deal level	DealScan
Deal amount	Natural log of deal value (in millions of USD)	
Lender avg. share	The tranche-amount-weighted average stake across all tranches within the deal, following the methodology of Blickle et al. (2022).	Authors' calculation, following Blickle, et al. (2022)
Domestic loan share	The natural logarithm of one plus the lender's dollar exposure to domestic loans. The exposure is calculated as the deal amount in U.S. dollars multiplied by the lender's percentage shareholding in the deal, where the shareholding is defined as the tranche-amount-weighted average stake across all tranches within the deal, following the methodology of Blickle et al. (2022). A loan is classified as domestic if the borrower's country matches the lender's operating country.	Authors' calculation, following Blickle, et al. (2022)
Domestic loan	Indicator equals one if the borrower and lead arranger have the same countries of incorporation, zero otherwise (Compustat variable FIC).	Global Compustat
Foreign loan share	The natural logarithm of one plus the lender's dollar exposure to foreign loans. The exposure is calculated as the deal amount in U.S. dollars multiplied by the lender's percentage shareholding in the deal, where the shareholding is defined as the tranche-amount-weighted average stake across all tranches within the deal, following the methodology of Blickle et al. (2022). A loan is classified as foreign if the borrower's country differs from the lender's operating country.	Authors' calculation, following Blickle, et al. (2022)
Foreign loan	Indicator equals one if the borrower and lead arranger have different countries of incorporation, zero otherwise (Compustat variable FIC).	Global Compustat
Maturity	Log of one plus the duration of the deal in months	DealScan
Prior relationship w/lender	Dummy variable equal to one if the borrower and lender have had at least one previous loan transaction in the dataset, and zero if the current loan is the first observed loan between the borrower-lender pair.	Authors' calculation
Secured loan	An indicator equal to one if the loan is secured, and zero otherwise	DealScan
Borrower characteristics		
Biodiversity score	Borrower's country-year level Biodiversity & Habitat (BDH) score from the Environmental Performance Index (EPI), which measures national efforts to protect terrestrial and marine ecosystems. Higher values indicate stronger biodiversity and habitat protection.	https://epi.yale.edu

Appendix A2 continued.

Climate change exposure	The relative frequency of climate change–related bigrams appearing in the firm's corporate earnings conference call transcripts, scaled by 1,000.	Sautner et al. (2023)
Firm size	Natural log of the borrower firm's total assets	Global Compustat
Leverage	Borrower firm's total debt scaled by total assets	Global Compustat
Polluter indicators	Sector-level indicators based on 2-digit NAICS and cross-industry emission intensity patterns following Crosignani et al. (2025). Extreme polluter equals one if the borrower is in the Utilities industry (NAICS 22); 0 otherwise. High polluter equals one if the borrower is in Mining/Oil/Gas (NAICS 21), Transportation (NAICS 48–49), or Agriculture/Forestry (NAICS 11); 0 otherwise. Medium-high polluter equals one if the borrower is in the chemicals, petroleum, or paper industries (NAICS 32); 0 otherwise. Medium polluter equals one if the borrower is in food, textiles, metals, machinery (NAICS 33); 0 otherwise. Low polluter equals one if the borrower is in the information and finance industries (NAICS 51-52); 0 otherwise.	Global Compustat
Profitability	Borrower firm's earnings before interest and taxes scaled by total assets	Global Compustat
EU ETS $_{Borrower}$	An indicator variable equal to one if the borrower's home country has adopted and implemented the European Union Emissions Trading System (ETS) in a given year, zero otherwise	www.carbontax.org
Lender characteristics		
Firm size $_{Lender}$	Natural log of the lender's total assets	Global Compustat
Leverage $_{Lender}$	Borrower lender's total debt scaled by total assets	Global Compustat
Profitability $_{Lender}$	Borrower lender's earnings before interest and taxes scaled by total assets	Global Compustat
EU ETS $_{Lender}$	An indicator variable equal to one if the lender's home country has adopted and implemented the European Union Emissions Trading System (ETS) in a given year, zero otherwise	www.carbontax.org
Borrower country characteristics		
Same legal origin	Dummy variable equal to one if both the borrower country and lender country share the same legal origin (both civil law or both common law), and zero if they have different legal origins.	World Bank
GDP growth	Annual percentage growth rate of real GDP per capita, measuring the year-over-year change in economic output per person	World Bank
Total emission	Country-level total anthropogenic greenhouse gas emissions measured in CO_2 equivalent	Emissions Database for Global Atmospheric Research (EDGAR)
Climate readiness	This variable measures a country's readiness to leverage private and public sector investment for adaptive actions to climate change	Notre Dame Global Adaptation Initiative

Appendix A3: Carbon Tax Implementation Year by Country

Country	Carbon Tax	ETS
Finland	1990	2005
Poland	1990	2005
Norway	1991	
Sweden	1991	2005
Denmark	1992	2005
Slovenia	1996	2005
Estonia	2000	2005
Latvia	2004	2005
Austria		2005
Belgium		2005
Cyprus		2005
Czech Republic		2005
Germany		2005
Greece		2005
Hungary		2005
Ireland		2005
Italy		2005
Lithuania		2005
Luxembourg		2005
Malta		2005
Netherlands		2005
Slovakia		2005
Bulgaria		2007
Romania		2007
Switzerland	2008	
Liechtenstein	2008	
New Zealand		2008
Iceland	2010	
Ireland	2010	2005
Ukraine	2011	
Japan	2012	
Croatia		2013
Kazakhstan		2013
United Kingdom	2013	2005
France	2014	2005
Mexico	2014	
Spain	2014	2005
Portugal	2015	2005
South Korea		2015
Chile	2017	
Colombia	2017	
Argentina	2018	
Canada	2019	
Singapore	2019	
South Africa	2019	
Mexico		2020

*Source:*www.carbontax.org

Appendix A4: Stacked DID Cohort Composition

Appendix A4 reports the number of treated and control firm-year observations in each treatment cohort within the pooled sample with non-missing carbon intensity observations. The matched sample contains the same cohort years but slightly fewer observations per cohort. We focus on three cohort years (2005, 2008, 2012), chosen to balance policy relevance and empirical power for causal identification.

From a policy perspective, these years corresponds to major institutional developments in global carbon pricing: (i) the launch of the EU ETS in 2005, the first large-scale multinational carbon market; (ii) the 2008 start of EU ETS Phase II with tighter caps, alongside the introduction of New Zealand's comprehensive ETS and Switzerland's carbon tax; and (iii) the 2012 expansion of the EU ETS to include aviation and the introduction of Japan's carbon tax amid broader global adoption of carbon taxes. Earlier adoption years (e.g., carbon taxes in the 1990s) yield too few treated observations for meaningful analysis, while later adoption years substantially shorten the post-treatment window. The chosen cohort structure, therefore, captures major institutional shifts in carbon pricing while preserving sufficient post-treatment data to support robust causal estimation.

Table A4. I: Cohort Composition

Cohort year	Policy events	Pooled sample (obs)	Matched sample (obs)
2005	EU ETS launch	3,357	2,525
2008	NZ ETS launch; Switzerland carbon tax	2,003	1,433
2012	Japan carbon tax; EU ETS aviation expansion	1,496	876
Total		6,856	4,834

Appendix A5: Biodiversity & Habitat (BDH) Score Construction

We use the Biodiversity & Habitat (BDH) issue category from the 2024 Environmental Performance Index (EPI), produced by the Yale Center for Environmental Law & Policy and CIESIN, to evaluate the extent to which countries safeguard natural ecosystems and biodiversity within their terrestrial and marine environments.[12]

The BDH category aggregates twelve sub-indicators**,** each normalized by EPI to a 0–100 scale (see EPI Technical Appendix, 2024). The sub-indicators and their respective weights are as follows: marine key biodiversity area protection (0.12), marine habitat protection (0.12), marine protection stringency (0.02), protected areas representativeness index (0.12), species protection index (0.16), terrestrial biome protection (0.10), protected area effectiveness (0.02), protected human land (0.02), red list index (0.12), species habitat index (0.08), and bioclimatic ecosystem resilience (0.02).

Weights are assigned by the EPI team based on data quality and the material importance of each indicator and sum to 100% for the BDH category. Weighted BDH scores are computed using these weights. When a country has missing ("NA") values for one or more indicators within the BDH category, the EPI proportionally reweights the remaining indicators so that the overall BDH score remains on a comparable 0–100 scale and is not biased downward by missing data. Higher BDH scores indicate stronger national performance in protecting biodiversity and habitat. Using the weighting and reweighting procedure outlined above, we calculate annual BDH scores for each country in our sample over the period 2002–2022.

[12] https://epi.yale.edu

Figure 1. Dynamic Effect of Carbon Tax on Borrower Carbon Intensity and Cost of Loans

Figure 1a: Carbon intensity of all loans

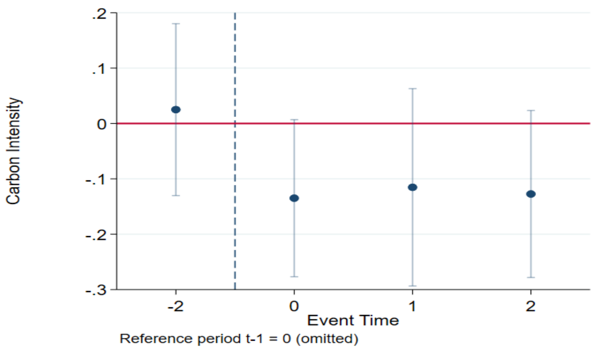


Figure 1b: Carbon intensity of foreign loans

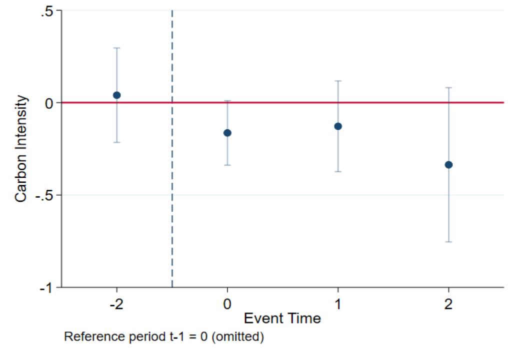


Figure 1c: Cost of all loans

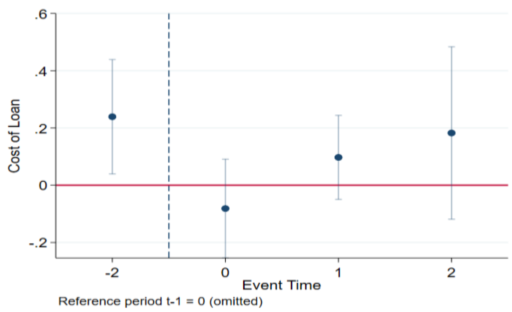
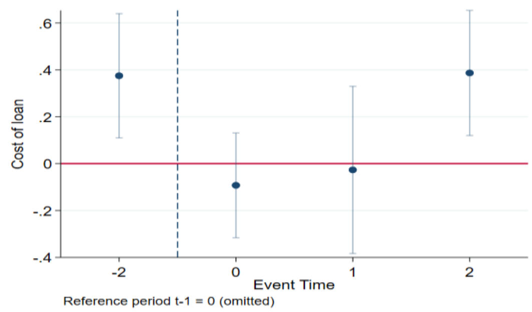


Figure 1d: Cost of foreign loans



Notes: Figures 1a,1b, 1c, and 1d report the dynamic effects of a carbon tax in borrowers' jurisdiction on borrowers' carbon intensity and cost of loans, respectively, estimated using a stacked difference-in-differences framework on a matched sample using regression equation (1). The treated and control borrower firms are propensity score-matched based on borrower country GDP growth and total emissions. These graphs are based on the coefficients with full control variables in Columns 3 and 6 of Table 4. We plot the coefficient estimates of dynamic indicators around the year of carbon tax implementation, with their 90% confidence intervals shown by the error bars. *Event (–2)* denotes two years before policy implementation*, Event* (0) the year of implementation, *Event (1)* one year after, and *Event (2)* two years after. The reference period is *Event* (–1), one year before implementation, which is omitted.

Table 1: Descriptive Statistics

Panel A: Summary statistics						
	Obs	Mean	SD	25%	Median	75%
Carbon and loan variables						
Carbon intensity (metric tons)	11,654	425.382	1225.074	7.567	22.041	157.092
Cost of loan (bps)	25,250	191.382	141.891	90.000	156.250	250.000
Foreign loan	25,250	0.264	0.441	0.000	0.000	1.000
Deal amount	25,250	5.866	1.401	4.942	5.858	6.898
Maturity	25,250	3.626	0.646	3.373	3.871	4.094
Secured loan	25,250	0.382	0.486	0.000	0.000	1.000
Lender avg. share (%)	25,249	30.783	22.949	15.962	23.807	37.624
Prior relationship w/ lender	25,250	0.733	0.443	0.000	1.000	1.000
Borrower characteristics						
$\text{PostCT}_{Borrower}$	25,250	0.027	0.162	0.000	0.000	0.000
$\text{Firm size}_{Borrower}$	25,250	7.910	1.920	6.574	7.832	9.217
$\text{Leverage}_{Borrower}$	25,250	0.326	0.223	0.165	0.306	0.452
$\text{Profitability}_{Borrower}$	25,250	0.073	0.081	0.036	0.068	0.109
$\text{Climate change exposure}_{Borrower}$	15,212	1.047	2.436	0.122	0.325	0.848
Lender characteristics						
PostCT_{Lender}	25,250	0.045	0.207	0.000	0.000	0.000
$\text{Firm size}_{Lender}$	22,169	13.622	1.026	13.109	13.866	14.473
Leverage_{Lender}	20,551	0.237	0.115	0.164	0.221	0.277
$\text{Profitability}_{Lender}$	21,764	0.020	0.009	0.014	0.020	0.025
Borrower/lender country characteristics						
$\text{EU ETS}_{Borrower}$	25,250	0.051	0.221	0.000	0.000	0.000
EU ETS_{Lender}	25,250	0.086	0.280	0.000	0.000	0.000
$\text{Same legal origin}_{Borrower\ country}$	25,250	0.855	0.352	1.000	1.000	1.000
$\text{GDP growth}_{Borrower\ country}$	24,839	1.441	2.140	0.761	1.798	2.190
$\text{Total emission}_{Borrower\ country}$	24,839	15.083	1.292	15.607	15.689	15.764
$\text{Biodiversity}_{Borrower\ country}$	25,250	44.510	8.927	42.340	44.344	44.880
$\text{Climate readiness}_{Borrower\ country}$	24,496	0.659	0.078	0.626	0.656	0.721

Continued.

Panel B: Correlation table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Carbon intensity	1																		
(2) Cost of loan	0.005	1																	
(3) PostCT$_{Borrower}$	-0.041*	-0.059*	1																
(4) PostCT$_{Lender}$	-0.026*	0.014*	0.381*	1															
(5) Foreign loan	0.039*	0.004	0.131*	0.247*	1														
(6) Deal amount	-0.049*	-0.207*	0.068*	0.071*	0.128*	1													
(7) Maturity	0.031*	0.125*	0.047*	0.038*	0.082*	0.114*	1												
(8) Secured loan	0.028*	0.461*	-0.044*	-0.037*	-0.027*	-0.153*	0.156*	1											
(9) Prior relationship w/ lender	0.007	-0.063*	-0.008	0.038*	-0.004	0.233*	0.006	-0.057*	1										
(10) Weighted Arranger holding	-0.032*	0.264*	-0.048*	-0.024*	-0.105*	-0.528*	-0.132*	0.219*	-0.158*	1									
(11) EU ETS$_{Borrower}$	-0.046*	0.046*	0.274*	0.119*	0.232*	0.170*	0.082*	-0.005	-0.021*	-0.061*	1								
(12) EU ETS$_{Lender}$	-0.003	0.082*	0.120*	0.207*	0.388*	0.123*	0.063*	0.002	0.014*	-0.067*	0.446*	1							
(13) Firm size$_{Borrower}$	-0.068*	-0.381*	0.067*	0.099*	0.161*	0.594*	-0.109*	-0.343*	0.267*	-0.387*	0.100*	0.100*	1						
(14) Leverage$_{Borrower}$	0.142*	0.178*	0.027*	0.047*	0.037*	0.080*	0.011	0.104*	0.086*	-0.044*	0.011	0.025*	0.047*	1					
(15) Profitability$_{Borrower}$	-0.033*	-0.172*	-0.029*	-0.036*	-0.012	0.138*	0.078*	-0.091*	0.061*	-0.128*	-0.003	-0.011	0.017*	-0.087*	1				
(16) Firm size$_{Lender}$	-0.066*	-0.027*	0.090*	0.131*	0.138*	0.362*	0.116*	-0.103*	0.111*	-0.183*	0.142*	0.224*	0.282*	0.045*	0.082*	1			
(17) Leverage$_{Lender}$	0.008	0.094*	-0.023*	-0.037*	-0.037*	0.079*	0.024*	0.126*	0.037*	-0.008	-0.005	-0.127*	0.016*	0.077*	0.060*	0.116*	1		
(18) Profitability$_{Lender}$	0.012	0.015*	-0.109*	-0.205*	-0.213*	-0.082*	-0.015*	0.080*	-0.022*	0.111*	-0.081*	-0.198*	-0.123*	-0.044*	0.001	-0.302*	0.320*	1	
(19) Biodiversity regulation$_{Borrower}$	0.033*	-0.036*	0.209*	0.037*	0.071*	0.072*	0.042*	0.008	-0.040*	-0.036*	0.407*	0.105*	-0.009	-0.003	-0.001	-0.016*	0.019*	-0.026*	1
(20) CC Reg Exposure$_{Borrower}$	0.425*	-0.038*	-0.006	0.049*	0.012	0.020*	-0.042*	-0.089*	0.044*	-0.024*	0.024*	0.031*	0.123*	0.046*	-0.068*	0.056*	-0.040*	-0.035*	-0.012

Notes: Table 1 Panel A presents the summary statistics for the key variables used in the regression analysis. The sample consists of deal-year observations from 2002 to 2022. *Carbon intensity* is the lender's share of weighted annual scope 1 CO_2 emissions (in metric tons per million US dollars of revenue) of borrowers in a lender's portfolio. The deal-level *cost of the loan* is the lender's exposure-weighted all-in spread drawn in basis points. *Foreign loan* is an indicator variable that equals one if the lender and borrower are from different countries and zero otherwise. *Deal amount* and maturity represent the log transformed loan size (in millions $) and *loan maturity* (in months). *Secured* loan is an indicator variable that takes a value of one if the loan is secured and zero otherwise. $PostCT_{Borrower}$ and $PostCT_{Lender}$ equal one from the year the carbon tax is introduced onward in the borrower's and lender's countries, respectively, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. All independent variables are calculated using values from the prior year. Definitions for all variables are provided in Appendix A2. Panel B presents the pairwise Pearson correlation coefficients between the key variables. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

Table 2: Syndicated Loan Deal Share (%) by Top 20 Lender and Borrower Countries

Rank	Lender country	% of total deal (USD)	Borrower country	% of total deal (USD)
1	United States	73.56	United States	69.78
2	United Kingdom	6.00	United Kingdom	5.72
3	Germany	4.33	France	2.86
4	Switzerland	3.00	Canada	2.67
5	France	2.81	Germany	2.43
6	Canada	2.66	Spain	1.78
7	Japan	2.54	Switzerland	1.70
8	Netherlands	2.15	Japan	1.20
9	Spain	0.83	Italy	1.15
10	Italy	0.51	Netherlands	1.04
11	Singapore	0.36	Ireland	0.89
12	Australia	0.33	Australia	0.87
13	Hong Kong	0.33	Mexico	0.74
14	Sweden	0.19	Singapore	0.65
15	Russia	0.10	Russia	0.51
16	China	0.70	Luxembourg	0.47
17	Mexico	0.06	Bermuda	0.47
18	India	0.05	Denmark	0.39
19	Saudi Arabia	0.05	Hong Kong	0.36
20	Luxembourg	0.03	Brazil	0.35

Notes: Table 2 presents the distribution of syndicated loan shares by the top 20 lender and borrower countries, measured as the percentage of total global syndicated loan volume (in USD) over the sample period. The left panel ranks countries by the share of total deal amounts disbursed by lenders headquartered in each country. The right panel ranks countries by the share of total deal amounts received by borrowers headquartered in each country, based on DealScan's borrower and lender location identifiers. Percentages reflect each country's cumulative contribution to global syndicated lending and borrowing, respectively. The sample period spans from 2002 to 2022.

Table 3: Stacked DID Estimation of Carbon Intensity and Cost of Loans: Post-Carbon Tax Evidence from Borrower Firms

Panel A: Matched stacked DID estimation for all loans						
Dependent variable	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
$PostCT_{Borrower}$ (1/0)	-0.126**	-0.138**	-0.119*	-0.060	0.000	0.015
	(0.014)	(0.020)	(0.059)	(0.513)	(0.998)	(0.867)
Deal amount	0.013***	0.006	0.005	-0.086***	-0.089***	-0.086***
	(0.009)	(0.410)	(0.521)	(0.000)	(0.000)	(0.000)
Maturity	0.007	-0.002	-0.002	0.058**	0.062**	0.060**
	(0.380)	(0.761)	(0.728)	(0.014)	(0.044)	(0.042)
Secured loan (1/0)	-0.017	-0.004	-0.011	0.337***	0.327***	0.318***
	(0.279)	(0.868)	(0.552)	(0.000)	(0.000)	(0.000)
Lender avg. share	0.001***	0.001**	0.001**	0.003***	0.003***	0.003***
	(0.001)	(0.022)	(0.036)	(0.000)	(0.000)	(0.000)
Firm $size_{Borrower}$	-0.058**	-0.017	-0.019	0.010	-0.018	-0.014
	(0.038)	(0.411)	(0.347)	(0.560)	(0.378)	(0.443)
$Leverage_{Borrower}$	0.039	-0.018	-0.029	0.094***	0.080***	0.081***
	(0.654)	(0.798)	(0.686)	(0.000)	(0.001)	(0.002)
$Profitability_{Borrower}$	-0.797**	-0.762***	-0.801***	-0.470***	-0.477***	-0.504***
	(0.030)	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)
Prior relation	0.000	-0.042***	-0.050***	-0.028*	-0.032	-0.028
w/ lender (1/0)	(0.975)	(0.003)	(0.002)	(0.052)	(0.172)	(0.202)
EU $ETS_{Borrower}$ (1/0)	-0.116*	-0.042	0.016	0.159**	0.128*	0.177**
	(0.095)	(0.431)	(0.767)	(0.031)	(0.075)	(0.022)
Firm $size_{Lender}$		0.154***	0.169***		-0.069	-0.056
		(0.003)	(0.001)		(0.220)	(0.388)
$Leverage_{Lender}$		-0.393**	-0.420**		0.286	0.259
		(0.039)	(0.037)		(0.205)	(0.272)
$Profitability_{Lender}$		0.171	-0.303		-2.949	-3.193
		(0.824)	(0.686)		(0.228)	(0.170)
EU ETS_{Lender} (1/0)		-0.097**	-0.132***		0.034	-0.012
		(0.026)	(0.003)		(0.667)	(0.829)
Borrower country characteristics						
GDP growth			0.018			-0.007
			(0.174)			(0.624)
Total emission			0.004			0.036
			(0.736)			(0.145)
Climate readiness			0.273			-1.126*
			(0.317)			(0.084)
Same legal origin (1/0)			-0.032			-0.084***
			(0.264)			(0.008)
Constant	4.075***	1.863***	1.484**	4.821***	6.060***	6.131***
	(0.000)	(0.009)	(0.030)	(0.000)	(0.000)	(0.000)
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,834	3,496	3,398	10,275	7,519	7,365
Adj. R-sq	0.984	0.987	0.986	0.743	0.749	0.751

Continued.

Table 3 continued.

Panel B: Matched stacked DID estimation for foreign loans

	Log (Carbon intensity)			Log (Cost of loan)		
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
$PostCT_{Borrower}$ (1/0)	-0.153*	-0.237**	-0.214**	-0.096	-0.097	-0.035
	(0.075)	(0.016)	(0.037)	(0.458)	(0.432)	(0.790)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	976	733	647	1,646	1,310	1,164
Adj. R^2	0.985	0.987	0.986	0.775	0.785	0.798

Notes: Table 3 presents matched stacked difference-in-differences (DID) estimates of the effects of carbon tax on borrower carbon intensity and foreign loan costs at the deal level. The dependent variable in Columns (1)-(3) is the natural log of Scope 1 greenhouse gas emissions, measured at the borrower firm-year level. The dependent variable in Columns (4)-(6) is the natural log of all-in-spread-drawn, representing the cost of the loan. The key independent variable, $PostCT_{Borrower}$, equals one for treated firms in years following the implementation of a carbon tax in their jurisdictions, and zero otherwise. Treatment cohorts are defined by the earliest adoption of either an emissions trading system (ETS) or a carbon tax and are estimated within ±2-year windows around the adoption date. Control cohorts are drawn from jurisdictions that did not adopt a carbon tax during the same period. The treated and the control firms are propensity scores matched by borrower country GDP growth and total emissions. Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All regressions include cohort × borrower, cohort × lender, and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table 3 Panel A. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table 4: Dynamic Effect of Carbon Tax on Borrower Carbon Intensity and Cost of Loans

Panel A: Dynamic matched stacked DID estimation for all loans						
Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCT$_{Borrower,\ t\text{-}2}$	0.128	0.058	0.037	0.086	0.115	0.195*
	(0.157)	(0.512)	(0.684)	(0.410)	(0.296)	(0.081)
PostCT$_{Borrower,\ t}$	-0.129***	-0.125*	-0.115	-0.140	-0.106	-0.066
	(0.002)	(0.081)	(0.132)	(0.194)	(0.399)	(0.586)
PostCT$_{Borrower,\ t+1}$	-0.091	-0.144*	-0.118	0.001	0.046	0.079
	(0.309)	(0.086)	(0.222)	(0.994)	(0.682)	(0.358)
PostCT$_{Borrower,\ t+2}$	-0.074	-0.117	-0.106	0.117	0.191	0.178
	(0.564)	(0.294)	(0.257)	(0.472)	(0.260)	(0.235)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,834	3,496	3,398	10,275	7,519	7,365
Adj. R^2	0.984	0.987	0.986	0.743	0.749	0.751
Panel B: Dynamic matched stacked DID estimation for foreign loans						
PostCT$_{Borrower,\ t\text{-}2}$	-0.002	0.036	0.045	0.152	0.202	0.375**
	(0.987)	(0.764)	(0.743)	(0.342)	(0.198)	(0.022)
PostCT$_{Borrower,\ t}$	-0.189***	-0.211**	-0.177*	-0.220	-0.210	-0.093
	(0.008)	(0.013)	(0.075)	(0.228)	(0.118)	(0.488)
PostCT$_{Borrower,\ t+1}$	-0.053	-0.197*	-0.140	-0.074	-0.107	-0.027
	(0.695)	(0.070)	(0.272)	(0.668)	(0.563)	(0.900)
PostCT$_{Borrower,\ t+2}$	-0.197	-0.329	-0.355*	0.294	0.302	0.387**
	(0.435)	(0.135)	(0.088)	(0.109)	(0.122)	(0.019)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	976	733	647	1,646	1,310	1,164
Adj. R^2	0.985	0.987	0.986	0.777	0.787	0.801

Notes: Table 4 presents dynamic event study estimates of the effects of carbon tax on borrower carbon intensity and the cost of foreign loans, estimated using a stacked difference-in-differences framework on a matched sample. Treatment and cohorts are defined as in Table 3. The dependent variable in Columns (1)-(3) is the natural log of Scope 1 greenhouse gas emissions, measured at the borrower firm-year level. The dependent variable in Columns (4)-(6) is the natural log of all-in-spread-drawn, representing the cost of the loan. Panels A and B report results for the full sample and the subsample of foreign loans, respectively. The key independent variables are event time indicators of $PostCT_{Borrower}$: $t-2$ (two years before), t (adoption year), $t+1$ (one year after), and $t+2$ (two years after). The omitted reference period is $t-1$ (one year before adoption). Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All regressions include cohort × borrower, cohort × lender, and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table 3 Panel A. The sample period spans from 2002 to 2022. Variable definitions are provided in Appendix A2. P-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table 5: Carbon-Tax Effects by Borrower Climate-Change Exposure: Carbon Intensity, and Cost of Loans

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All loans: High-exposure borrower (≥ median)						
$PostCT_{Borrower}$ (1/0)	-0.177***	-0.191***	-0.247***	-0.105	-0.109	-0.032
	(0.004)	(0.007)	(0.003)	(0.330)	(0.412)	(0.802)
N	4,332	3,142	3,051	7,920	5,744	5,643
Adj. R^2	0.985	0.987	0.987	0.739	0.744	0.746
Panel B: Foreign loans: High-exposure borrower (≥ median)						
$PostCT_{Borrower}$ (1/0)	-0.039	-0.208*	-0.299**	-0.152	-0.129	-0.076
	(0.744)	(0.088)	(0.042)	(0.325)	(0.461)	(0.589)
N	589	474	406	907	750	671
Adj. R^2	0.984	0.984	0.983	0.799	0.799	0.812
Panel C: All loans: Low-exposure borrower (< median)						
$PostCT_{Borrower}$ (1/0)	-0.153**	-0.168*	-0.203**	-0.092	-0.015	0.121
	(0.038)	(0.083)	(0.043)	(0.176)	(0.883)	(0.250)
N	1,829	1,243	1,185	6,565	4,727	4,554
Adj. R^2	0.988	0.988	0.988	0.765	0.767	0.765
Panel D: Foreign loans: Low-exposure borrower (< median)						
$PostCT_{Borrower}$ (1/0)	-0.316**	-0.263*	-0.294	-0.066	-0.073	0.099
	(0.032)	(0.073)	(0.112)	(0.553)	(0.592)	(0.496)
N	598	385	335	1,394	1,043	895
Adj. R^2	0.990	0.989	0.989	0.802	0.795	0.784
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 5 presents deal-level estimates of the effects of a borrower-country carbon tax on loan carbon intensity and cost of loan, classified by borrowers' climate change exposure. The dependent variable in Columns (1)-(3) is the carbon intensity of the loan, measured as the borrower's annual Scope 1 CO_2 emissions (in metric tons per million US dollars of revenue) at the deal level. The dependent variable in Columns (4)-(6) is the cost of the loan, measured as the natural log of the all-in-spread-drawn of the deal issued by the syndicate's lead arranger in a given year. Panels A and C report results for all loans, and Panels B and D report results for foreign loans. Panels A and B (Panels C and D) restrict the sample to borrowers with high-exposure, i.e., ≥median (low-exposure, i.e., <median), respectively. Developed by Sautner et al. (2023), borrower climate-change exposure is constructed as the relative frequency of climate change–related bigrams in corporate earnings conference-call transcripts. $PostCT_{Borrower}$ equals one from the year the carbon tax is introduced in the borrower's country onward, and zero otherwise. Treatment cohorts follow a stacked-DID design: treated cohorts are defined by the borrower-country's first adoption of either an emissions trading system (ETS) or a carbon tax, and effects are estimated within ±2-year event windows around the adoption year; control cohorts are drawn from jurisdictions that do not adopt a carbon tax within the corresponding window. For brevity, we report only the main variables of interest; Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All panels include cohort × borrower, cohort × lender, and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table 3 Panel A. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table 6: Borrowers' Industry, Carbon Intensity, and Cost of Loans

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Stacked DID estimation for all loans						
Extreme polluter×PostCT$_{Borrower}$	-0.750**	-0.790**	-0.857***	-0.347**	-0.437***	-0.429***
	(0.012)	(0.012)	(0.008)	(0.022)	(0.004)	(0.006)
High polluter×PostCT$_{Borrower}$	-0.304	-0.506	-0.449	-0.066	-0.213*	-0.198
	(0.457)	(0.341)	(0.401)	(0.641)	(0.072)	(0.008)
Medium-high polluter×PostCT$_{Borrower}$	-0.224	-0.071	0.024	-0.026	-0.143	-0.114
	(0.620)	(0.868)	(0.949)	(0.858)	(0.132)	(0.231)
Medium polluter×PostCT$_{Borrower}$	-0.100	0.055	0.051	0.076	-0.031	-0.030
	(0.755)	(0.888)	(0.888)	(0.610)	(0.746)	(0.776)
Low polluter× PostCT$_{Borrower}$	0.084	0.052	-0.002	0.246*	0.178	0.182
	(0.719)	(0.850)	(0.994)	(0.074)	(0.171)	(0.160)
PostCT$_{Borrower}$ (1/0)	-0.141	-0.056	0.082	-0.251*	-0.104	-0.014
	(0. 260)	(0. 730)	(0.542)	(0.085)	(0.247)	(0.874)
Extreme polluter	4.498***	4.506***	4.520***	-0.144***	-0.182***	-0.189***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High polluter	2.780***	2.782***	2.763***	0.018**	0.033***	0.035***
	(0.000)	(0.000)	(0.000)	(0.048)	(0.002)	(0.000)
Medium-high polluter	1.940***	1.970***	1.855***	0.014	0.012	-0.009
	(0.000)	(0.000)	(0.000)	(0.730)	(0.731)	(0.608)
Medium polluter	0.219***	0.195***	0.181***	-0.063***	-0.061***	-0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low polluter	-2.530***	-2.490***	-2.493***	-0.009	-0.018*	-0.018***
	(0.000)	(0.000)	(0.000)	(0.516)	(0.098)	(0.004)
Deal & borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,307	6,411	6,172	20,897	16,549	16,045
Adj. R^2	0.738	0.743	0.749	0.524	0.531	0.531

Continued.

Table 6 continued.

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Stacked DID estimation for foreign loans						
Extreme polluter× $PostCT_{Borrower}$	-0.341	-0.524	-0.594	-0.726***	-0.767***	-0.751***
	(0.451)	(0.237)	(0.201)	(0.000)	(0.000)	(0.000)
High polluter× $PostCT_{Borrower}$	-0.551	-0.826	-0.726	-0.251*	-0.251	-0.252
	(0.338)	(0.213)	(0.275)	(0.067)	(0.151)	(0.172)
Medium-high polluter×	-1.290***	-1.077**	-0.893**	-0.232	-0.267*	-0.202
$PostCT_{Borrower}$	(0.002)	(0.010)	(0.040)	(0.106)	(0.060)	(0.124)
Medium polluter× $PostCT_{Borrower}$	-0.004	0.065	-0.037	-0.113	-0.100	-0.076
	(0.994)	(0.911)	(0.944)	(0.472)	(0.584)	(0.683)
Low polluter× $PostCT_{Borrower}$	0.361	0.262	0.254	0.178	0.222	0.249
	(0.310)	(0.500)	(0.495)	(0.233)	(0.183)	(0.160)
$PostCT_{Borrower}$ (1/0)	-0.085	-0.093	-0.175	-0.000	-0.015	0.040
	(0.706)	(0.690)	(0.428)	(0.999)	(0.899)	(0.736)
Extreme polluter	4.189***	4.335***	4.376***	-0.034	0.035	0.028
	(0.000)	(0.000)	(0.000)	(0.657)	(0.483)	(0.513)
High polluter	2.679***	2.680***	2.652***	-0.058	-0.033	-0.032
	(0.000)	(0.000)	(0.000)	(0.115)	(0.296)	(0.174)
Medium-high polluter	2.748***	2.674***	2.485***	0.113*	0.142**	0.073*
	(0.000)	(0.000)	(0.000)	(0.057)	(0.013)	(0.084)
Medium polluter	0.293	0.398***	0.439***	-0.112**	-0.097**	-0.111**
	(0.133)	(0.006)	(0.000)	(0.043)	(0.014)	(0.010)
Low polluter	-2.655***	-2.588***	-2.659***	-0.007	0.011	-0.009
	(0.000)	(0.000)	(0.000)	(0.862)	(0.752)	(0.786)
Deal & borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,148	1,716	1,492	4,429	3,748	3,280
Adj. R^2	0.734	0.738	0.744	0.570	0.579	0.579

Notes: Table 6 presents deal-level stacked DID regression estimates examining the effects of borrower firms' industries in jurisdictions with a carbon tax on the carbon intensity and cost of loans. The dependent variable in Columns (1)-(3) is the carbon intensity of the loan, measured as the borrower's annual Scope 1 CO_2 emissions (in metric tons per million US dollars of revenue) at the deal level. The dependent variable in Columns (4)-(6) is the cost of the loan, measured as the natural log of the all-in-spread-drawn of the deal issued by the syndicate's lead arranger in a given year. Panels A and B report results for the full sample and the subsample of foreign loans, respectively. Borrowers are classified into six emission-intensity industries based on 2-digit NAICS codes: extreme polluter (22), high polluter (11, 21, 48–49), medium-high polluter (32), medium polluter (31, 33), and low polluter (51–52) following Crosignani et al. (2025). Treatment and cohorts are defined as in Table 5. Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All regressions include cohort × lender and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table 3 Panel A. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. P-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table 7: Environmental Stringency Across Borrower Countries, Carbon Intensity, and Cost of Loans

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Stacked DID estimation for all loans						
Biodiversity score$_{Borrower}$	0.008***	0.007**	0.011***	0.002	-0.001	0.002
×PostCT$_{Borrower}$	(0.001)	(0.027)	(0.002)	(0.709)	(0.828)	(0.724)
Biodiversity score$_{Borrower}$	-0.001	0.000	-0.007	-0.003	-0.001	-0.003
	(0.698)	(0.817)	(0.120)	(0.186)	(0.788)	(0.587)
PostCT$_{Borrower}$	-0.530***	-0.503***	-0.746***	-0.176	0.023	-0.097
	(0.000)	(0.006)	(0.001)	(0.533)	(0.951)	(0.807)
N	6,856	4,960	4,803	16,220	11,904	11,604
Adj. R^2	0.984	0.986	0.985	0.739	0.741	0.742
Panel B: Stacked DID estimation for foreign loans						
Biodiversity score$_{Borrower}$	0.003	0.003	0.008*	-0.003	-0.004	0.004
×PostCT$_{Borrower}$	(0.349)	(0.397)	(0.077)	(0.703)	(0.622)	(0.696)
Biodiversity score$_{Borrower}$	0.001	0.001	-0.010	-0.001	0.002	-0.005
	(0.606)	(0.905)	(0.215)	(0.654)	(0.416)	(0.562)
PostCT$_{Borrower}$	-0.283	-0.401**	-0.687**	0.036	0.071	-0.252
	(0.126)	(0.031)	(0.015)	(0.938)	(0.894)	(0.674)
N	1,392	1,016	878	2,612	2,047	1,778
Adj. R^2	0.983	0.985	0.984	0.780	0.781	0.784
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 7 presents deal-level stacked DID regression estimates examining the effects of additional formal environmental stringency in jurisdictions with an existing carbon tax on the carbon intensity and cost of loans. Panels A and B report results for the full sample and the subsample of foreign loans, respectively. The dependent variable in Columns (1)-(3) is the carbon intensity of the loan, measured as the borrower's annual Scope 1 CO_2 emissions (in metric tons per million US dollars of revenue) at the deal level. The dependent variable in Columns (4)-(6) is the cost of the loan, measured as the natural log of the all-in-spread-drawn of the deal issued by the syndicate's lead arranger in a given year. *Biodiversity score$_{Borrower}$* is the borrower's country-year level Biodiversity & Habitat (BDH) score from the Environmental Performance Index (EPI), which measures national efforts to protect terrestrial and marine ecosystems. Higher values indicate stronger biodiversity and habitat protection. The key independent variable is the interaction term *Biodiversity score$_{Borrower}$* × *PostCT$_{Borrower}$*, where *PostCT$_{Borrower}$* equals one from the year the carbon tax is introduced in the borrower's country onward, and zero otherwise. Treatment and cohorts are defined as in Table 5. All regressions in Panels A and B include fixed effects for borrower firm, lender firm, and year. Standard errors are clustered at the borrower country level. The sample period spans from 2002 to 2022. All models control for the same set of variables as in Table 3 Panel A. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. P-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table 8: Carbon Tax and Cross-Border Lending: Spillover Effects on Foreign Loan Share

Dependent variable:	Foreign loan share $_{t+1}$			Foreign loan share $_{t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCT$_{Borrower}$	-0.086			-0.061**		
	(0.136)			(0.044)		
PostCT$_{Lender}$		0.074			0.052*	
		(0.138)			(0.075)	
PostCT$_{Borrower\ \&\ Lender}$			0.038			0.074**
			(0.602)			(0.032)
Borrower control	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,185	3,185	3,185	3,279	3,279	3,279
Adj. R^2	0.760	0.761	0.759	0.878	0.878	0.877

Notes: Table 8 examines the spillover effect of borrower-country carbon taxation on foreign lenders' loan allocation decisions. The dependent variable, *foreign loan share*, is measured as the aggregated USD exposure of a lender to borrowers in foreign countries, weighted by the lender's predicted loan holdings at the lender–borrower country-year level. The 1-year and 3-year forward foreign loan share measures represent the foreign loan share in the first year and the average annual foreign loan share over the three years following the adoption of the carbon tax, respectively. $PostCT_{Borrower}$ equals one from the year the carbon tax is introduced in the borrower's country onward, and zero otherwise. $PostCT_{Lender}$ equals one from the year the carbon tax is introduced in the lender's country onward, and zero otherwise. $PostCT_{Borrower\ \&\ Lender}$ is an indicator equal to one if, in the same year a carbon tax is introduced in the borrower's country, the lender's country also has an active carbon tax, and zero otherwise. All regressions include borrower firm, lender firm, and year fixed effects. Standard errors are clustered at the borrower country level. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. All models control for the same set of variables used in Table 3 Panel A Column (3), except *lender avg. share* variable. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table 9: Carbon Tax and Domestic Lending: Exposure within Borders

Panel A: Domestic carbon tax, carbon intensity, and cost of loan

Dependent variable:	Carbon intensity			Cost of loan		
	(1)	(2)	(3)	(4)	(5)	(6)
$PostCT_{Borrower}$	-0.265***	-0.262***	-0.505**	-0.006*	0.364***	0.190
	(0.001)	(0.027)	(0.023)	(0.969)	(0.003)	(0.378)
Deal-level control	Yes	Yes	Yes	Yes	Yes	Yes
Borrower control	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,957	3,501	3,501	12,462	8,860	8,860
Adj. R^2	0.984	0.985	0.985	0.747	0.753	0.753

Panel B: Domestic lender's participation

Dependent variable:	Domestic loan share $_{t+1}$	Domestic loan share $_{t+3}$
	(1)	(2)
$PostCT_{Borrower}$	0.448***	0.277**
	(0.006)	(0.017)
Borrower controls	Yes	Yes
Lender controls	Yes	Yes
Country-level controls	Yes	Yes
Borrower firm FE	Yes	Yes
Lender firm FE	Yes	Yes
Year FE	Yes	Yes
N	11,660	11,876
Adj. R^2	0.737	0.843

Notes: Table 9 examines domestic lending outcomes following the implementation of a carbon tax. Panel A reports stacked DID estimates of the carbon tax effects on borrower-level carbon intensity and loan costs, as shown in Table 3, Panel A. The dependent variables are the log of Scope 1 emissions (Columns 1–3) and the log of all-in-spread-drawn (Columns 4–6). Panel B assesses lenders' domestic loan allocations after the adoption of a carbon tax in their home country. The dependent variable, *lender's domestic loan share*, is calculated as the lender's USD exposure to home-country borrowers, weighted by predicted holdings at the lender–borrower country-year level. The 1-year and 3-year forward measures refer to the first year and the average annual share over the three years post-adoption, respectively. $PostCT_{Borrower}$ equals one from the year of carbon tax adoption in the borrower's country onward. All regressions include cohort × borrower, cohort × lender, and cohort × year fixed effects (Panel A), and borrower, lender, and year fixed effects (Panel B). Standard errors are clustered at the borrower country level. All models use controls from Table 3, Panel A, Column 3. Panel B includes all controls except *lender avg. share* variable. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions appear in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Online Appendix B

"The unintended consequences of climate policy: Carbon taxes, regulatory arbitrage, and competition in lending"

The following table provides an overview of the contents of Online Appendix B and how they relate to the main body of the paper.

Content Index	Topic	In-Text Reference
Online Appendix B	*Robustness checks*	
Table OAB.I	Alternative measures of carbon emission	Section 4.3
Table OAB.II	Pooled stacked DID regression	Section 4.3
Table OAB.III	Two-way fixed effects DID regression	Section 4.3
Table OAB.IV	Various fixed-effect regressions	Section 4.3
Table OAB.V	Subsample analyses	Section 4.3
Table OAB.VI	Borrowers classified by prior-year carbon intensity quintiles	Section 5.2

Appendix B: Alternative Model Specifications

B.1 Matched sample stacked DID

To construct a matched sample cohort, we match treated and control firms prior to stacking using propensity scores based on pre-treatment borrower-country characteristics, GDP growth, and total emissions, which are relevant to carbon intensity and loan costs. Matching is conducted separately within each treatment cohort using data from one year before policy implementation, with 1:1 nearest-neighbor matching and calipers of 0.1-0.2. This procedure ensures that treated and control firms are comparable on observable economic and environmental characteristics that may jointly influence policy adoption and firm outcomes, tightening the parallel trends requirement to hold within cohort sets. This matching design addresses potential selection bias, strengthens comparability, and ensures robustness to reasonable sources of omitted variable bias.

B.2 Two-way fixed effects DID

We use the following two-way fixed effects difference-in-differences (TWFE-DID) framework to analyze the effect of carbon tax in the borrower's jurisdiction on the carbon intensity and the cost of syndicated foreign lending. Our unbalanced panel regressions, estimated at the lender-borrower-deal-year level, are as follows:

$$Y_{lender,borrower,deal,t} = \alpha + \beta_1 PostCT_{borrower,t} \times Foreign\ loan_{lender,borrower,deal,t} + \beta_2 PostCT_{borrower,t} + \beta_3 Foreign\ loan_{lender,borrower,deal,t} + \gamma X_{\mathrm{deal},t} + \delta Z_{lender,borrower,t-1} + \theta D_{lender,borrower,t} + \varepsilon_{lender,borrower,deal,t} \tag{B2}$$

Table OAB.III reports the corresponding DID estimation results at the deal level. Columns (1) to (3) present estimates for *Log (Carbon intensity)*, while Columns (4) to (6) present estimates for *Log (Cost of loan)*. Column (1) includes deal- and borrower-level controls; Column (2) adds lender characteristics; and Column (3) incorporates borrower-country characteristics. The specifications in Columns (4) to (6) follow the same progression. All regressions include borrower, lender, and year fixed effects to control for unobserved firm-specific heterogeneity and common time trends. Standard errors are clustered at the borrower-country level to account for cross-sectional dependence arising from shared regulatory environments.

Table OAB.I: Robustness checks: Alternative measures of Carbon Emission

	Full sample			Foreign loan sample		
Dependent variable:	|Scope 1 emission|	Ln (|Scope 1 emission|)	Ln (Scope 1 emission/total asset)	|Scope 1 emission|	Ln (|Scope 1 emission|)	Ln (Scope 1 emission/total asset)
	(1)	(2)	(3)	(4)	(5)	(6)
$PostCT_{Borrower}$	-1016380.938**	-0.234***	-0.237**	-589,430.313	-0.311***	-0.298**
	(0.019)	(0.004)	(0.011)	(0.439)	(0.003)	(0.012)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,803	4,803	3,223	878	878	537
Adj. R^2	0.967	0.987	0.920	0.983	0.988	0.985

Notes: Table OAB.I presents the pooled stacked DID estimates of the effects of a carbon tax on borrower carbon for various carbon emission measures. The dependent variables in Columns (1) and (2) are the raw and the natural logarithm of the absolute emission reported in tons of CO_2 equivalent emissions, respectively, measured at the borrower firm-year level. Columns (3) and (6) are the absolute emission normalized by the firm's annual total assets. The key independent variable, $PostCT_{Borrower}$, equals one for treated firms in years following the implementation of a carbon tax in their jurisdictions, and zero otherwise. Treatment cohorts are defined by the earliest adoption of either an emissions trading system (ETS) or a carbon tax and are estimated within ±2-year windows around the adoption date. Control cohorts are drawn from jurisdictions that did not adopt a carbon tax during the same period. Columns (1)-(3) report results for the full sample, and Columns (4)-(6) report results from the subsample of foreign loans, respectively. All regressions include deal-level, borrower, lender characteristics, and country-level controls. All models control for the same set of variables as in Table 3, Panel A, Column 3. Standard errors are clustered at the borrower-country level. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table OAB.II: Pooled sample stacked DID Estimation of Carbon Intensity and Cost of Loans

Panel A: Sample of all loans						
Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCT$_{Borrower}$	-0.120**	-0.140**	-0.166**	-0.080	-0.052	0.022
	(0.021)	(0.011)	(0.018)	(0.293)	(0.580)	(0.806)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,856	4,960	4,803	16,220	11,904	11,604
Adj. R^2	0.984	0.986	0.985	0.739	0.741	0.742
Panel B: Sample of foreign loans						
PostCT$_{Borrower}$	-0.141*	-0.242***	-0.266***	-0.126	-0.157	-0.053
	(0.072)	(0.001)	(0.005)	(0.215)	(0.152)	(0.655)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,392	1,016	878	2,612	2,047	1,778
Adj. R^2	0.983	0.986	0.984	0.780	0.781	0.784

Notes: Table OAB. II presents the pooled stacked DID estimates of the effects of carbon tax on borrower carbon intensity and loan costs at the deal level. The dependent variable in Columns (1)-(3) is the natural log of Scope 1 greenhouse gas emissions, measured at the borrower firm-year level. The dependent variable in Columns (4)-(6) is the natural log of all-in-spread-drawn, representing the cost of the loan. The key independent variable, *PostCT$_{Borrower}$*, equals one for treated firms in years following the implementation of a carbon tax in their jurisdictions, and zero otherwise. Treatment cohorts are defined by the earliest adoption of either an emissions trading system (ETS) or a carbon tax and are estimated within ±2-year windows around the adoption date. Control cohorts are drawn from jurisdictions that did not adopt a carbon tax during the same period. Panels A and B report results for the full sample and the subsample of foreign loans, respectively. Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All regressions include cohort × borrower, cohort × lender, and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table 3 Panel A. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table OAB.III: TWFE DID Estimation of Carbon Intensity and Cost of Loans: Post-Carbon Tax Evidence from Borrower Firms

Dependent Variable	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: TWFE DID estimation for the full sample						
PostCT$_{Borrower}$ (1/0)	0.105	0.082	0.098	-0.136	-0.100*	-0.057
	(0.309)	(0.442)	(0.352)	(0.110)	(0.070)	(0.247)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Borrower firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10,418	8,004	7,770	22,474	17,473	17,029
Adj. R-sq	0.948	0.950	0.949	0.682	0.679	0.680
Panel B: TWFE DID estimation for foreign loan sample						
PostCT$_{Borrower}$	-0.055	-0.163	-0.147	-0.013	-0.062	-0.034
	(0.541)	(0.115)	(0.143)	(0.884)	(0.436)	(0.710)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Borrower firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,903	2,194	1,975	4,952	3,853	3,453
Adj. R^2	0.957	0.957	0.956	0.715	0.730	0.735
Panel C: TWFE DID estimation for the full sample with foreign loan interaction term						
PostCT$_{Borrower}$× Foreign loan	-0.090	-0.228***	-0.218***	0.185**	0.049	0.029
	(0.232)	(0.006)	(0.009)	(0.041)	(0.411)	(0.602)
PostCT$_{Borrower}$	0.171	0.258**	0.265**	-0.267**	-0.141*	-0.081
	(0.212)	(0.045)	(0.035)	(0.014)	(0.072)	(0.259)
Foreign loan (1/0)	0.008	0.034**	0.037	0.032	0.011	0.011
	(0.627)	(0.031)	(0.101)	(0.125)	(0.510)	(0.620)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Borrower firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10,418	8,004	7,770	22,474	17,473	17,029
Adj. R^2	0.948	0.950	0.949	0.682	0.679	0.680

Continued.

Table OAB.III continued.

Notes: Table OAB.III presents deal-level TWFE difference-in-difference (DID) regression estimates examining the effects of carbon tax in the borrower's country on the carbon intensity and cost of foreign loans. The dependent variable in Columns (1)-(3) is the loan carbon intensity, measured as the borrower's annual Scope 1 CO_2 emissions (in metric tons per million US dollars of revenue) at the deal level. The dependent variable in Columns (4)-(6) is the cost of the loan, measured as the natural log of the all-in-spread-drawn of the deal issued by the syndicate's lead arranger in a given year. Panels A and B report results for all loans and foreign loans, respectively. Panel C reports the results for the full sample, where the key independent variable is $PostCT_{Borrower}$ × *Foreign loan*, the interaction of a carbon tax indicator and a foreign loan indicator. $PostCT_{Borrower}$ equals one from the year the carbon tax is introduced in the borrower's country onward, and zero otherwise. *Foreign loan* equals one if the lender and borrower are from different countries, and zero otherwise. The deal-level regressions include fixed effects for borrower firm, lender firm, and year. Standard errors are clustered at the borrower country level. The sample period spans from 2002 to 2022. For brevity, we report only the variables of primary interest. All models include the same set of controls as shown in Table 3, Panel A. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table OAB. IV: Robustness checks: Various Fixed-effect Regressions

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	All loans		Foreign loans	All loans		Foreign loans
	(1)	(2)	(3)	(4)	(5)	(6)
$PostCT_{Borrower}$	-0.145**	-0.144**	-0.220***	0.003	0.015	-0.073
	(0.012)	(0.022)	(0.005)	(0.978)	(0.876)	(0.556)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender FE	No	No	No	No	No	No
Cohort × lender country FE	No	Yes	No	No	Yes	No
N	4,990	4,962	988	11,881	11,850	1,907
Adj. R^2	0.985	0.985	0.985	0.727	0.728	0.778

Notes: OAB. IV presents the pooled stacked DID estimates of the effects of a carbon tax on borrower carbon intensity and loan costs at the deal level, for various fixed effects and subsample tests. The dependent variable in Columns (1)-(3) is the natural log of Scope 1 greenhouse gas emissions, measured at the borrower firm-year level. The dependent variable in Columns (4)-(6) is the natural log of all-in-spread-drawn, representing the cost of the loan. The key independent variable, $PostCT_{Borrower}$, equals one for treated firms in years following the implementation of a carbon tax in their jurisdictions, and zero otherwise. Treatment cohorts are defined by the earliest adoption of either an emissions trading system (ETS) or a carbon tax and are estimated within ±2-year windows around the adoption date. Control cohorts are drawn from jurisdictions that did not adopt a carbon tax during the same period. Columns (1)-(2) and (4)-(5) report results for the full sample, and Columns (3) and (6) report results from the subsample of foreign loans, respectively. All regressions include deal-level, borrower, lender characteristics, and country-level controls. All models control for the same set of variables as in Table 3, Panel A, Column 3. Standard errors are clustered at the borrower-country level. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table OAB. V: Robustness checks: Subsamples of Lenders and Borrowers

Panel A: Sample excluding US borrowers						
Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
$PostCT_{Borrower}$	-0.376***	-0.413***	-0.393***	-0.174*	-0.030	-0.044
	(0.000)	(0.000)	(0.006)	(0.054)	(0.755)	(0.685)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender country FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,860	1,364	1,102	3,172	2,340	1,805
Adj. R^2	0.804	0.816	0.815	0.481	0.503	0.512
Panel B: Sample excluding US lenders						
$PostCT_{Borrower}$	-0.172***	-0.170**	-0.177**	-0.149	-0.041	0.018
	(0.000)	(0.017)	(0.027)	(0.252)	(0.774)	(0.900)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender country FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,427	1,003	937	2,671	1,984	1,807
Adj. R^2	0.981	0.982	0.981	0.773	0.761	0.766
Panel C: Sample excluding EU borrowers						
$PostCT_{Borrower}$	0.234**	1.202***	1.108***	-0.703***	-0.284***	-0.308***
	(0.027)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort × borrower industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort ×lender country FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,676	5,869	5,653	19,850	15,655	15,189
Adj. R^2	0.813	0.820	0.819	0.513	0.526	0.526

Continued.

Table OAB. V Continued.

Notes: Table OAB. V presents the pooled stacked difference-in-differences (DID) estimates of the effects of a carbon tax on borrower carbon intensity and loan costs at the deal level, using subsamples that exclude key borrower or lender groups. The dependent variable in Columns (1)-(3) is the natural log of Scope 1 greenhouse gas emissions, measured at the borrower firm-year level. The dependent variable in Columns (4)-(6) is the natural log of all-in-spread-drawn, representing the cost of the loan. The key independent variable, $PostCT_{Borrower}$, equals one for treated firms in years following the implementation of a carbon tax in their jurisdictions, and zero otherwise. Panel A excludes U.S. borrowers; Panel B excludes U.S. lenders; and Panel C excludes EU borrowers. Treatment cohorts are defined by the earliest adoption of either an emissions trading system (ETS) or a carbon tax and are estimated within ±2-year windows around the adoption date. Control cohorts are drawn from jurisdictions that did not adopt a carbon tax during the same period. The treated and the control firms are propensity scores matched by borrower country GDP growth and total emissions. Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All regressions include cohort × borrower industry, cohort × lender country, and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table IA1 Panel A. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Table OAB. VI: Carbon-Tax Effects by Borrowers' Prior-Year Carbon Intensity Quintiles

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Stacked DID estimation for all loans						
Carbon intensity $Q2_{t-1}\times$	-0.111	-0.192*	-0.199*	-0.103	-0.055	-0.054
$PostCT_{Borrower}$	(0.258)	(0.070)	(0.066)	(0.473)	(0.773)	(0.781)
Carbon intensity $Q3_{t-1}\times$	-0.097	-0.050	-0.047	-0.024	0.093	0.066
$PostCT_{Borrower}$	(0.194)	(0.536)	(0.571)	(0.898)	(0.727)	(0.807)
Carbon intensity $Q4_{t-1}\times$	-0.351***	-0.276*	-0.233	-0.193	-0.178	-0.084
$PostCT_{Borrower}$	(0.007)	(0.067)	(0.105)	(0.306)	(0.402)	(0.678)
Carbon intensity $Q5_{t-1}\times$	-0.275***	-0.293***	-0.301***	0.018	0.075	0.046
$PostCT_{Borrower}$	(0.008)	(0.009)	(0.010)	(0.924)	(0.719)	(0.829)
$PostCT_{Borrower}$ (1/0)	0.019	-0.009	-0.037	-0.039	-0.143	-0.046
	(0.737)	(0.899)	(0.628)	(0.744)	(0.330)	(0.761)
Carbon intensity $Q2_{t-1}$	0.510***	0.495***	0.495***	-0.065	-0.028	-0.039
	(0.000)	(0.000)	(0.000)	(0.371)	(0.711)	(0.606)
Carbon intensity $Q3_{t-1}$	0.704***	0.657***	0.649***	-0.094	-0.093	-0.101
	(0.000)	(0.000)	(0.000)	(0.261)	(0.260)	(0.232)
Carbon intensity $Q4_{t-1}$	0.858***	0.733***	0.720***	-0.115	-0.155	-0.184*
	(0.000)	(0.000)	(0.000)	(0.272)	(0.149)	(0.088)
Carbon intensity $Q5_{t-1}$	1.131***	1.099***	1.084***	-0.190	-0.402***	-0.363***
	(0.000)	(0.000)	(0.000)	(0.173)	(0.004)	(0.010)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,308	4,562	4,425	6,453	4,671	4,530
Adj. R^2	0.985	0.987	0.986	0.736	0.749	0.751

Continued.

Table OAB. VI continued.

Dependent variable:	Log (Carbon intensity)			Log (Cost of loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
<u>Panel B: Stacked DID estimation for foreign loans</u>						
Carbon intensity $Q2_{t-1}$×	-0.265	-0.348***	-0.390***	0.055	0.124	0.181
$PostCT_{Borrower}$	(0.218)	(0.008)	(0.005)	(0.797)	(0.632)	(0.477)
Carbon intensity $Q3_{t-1}$×	-0.194*	-0.129	-0.134	-0.059	0.215	0.172
$PostCT_{Borrower}$	(0.090)	(0.343)	(0.342)	(0.815)	(0.508)	(0.580)
Carbon intensity $Q4_{t-1}$×	-0.775***	-0.808***	-0.704***	-0.415	-0.397	0.016
$PostCT_{Borrower}$	(0.005)	(0.002)	(0.004)	(0.133)	(0.212)	(0.949)
Carbon intensity $Q5_{t-1}$×	-0.496***	-0.527***	-0.545***	0.012	0.174	0.223
$PostCT_{Borrower}$	(0.003)	(0.001)	(0.001)	(0.959)	(0.497)	(0.373)
$PostCT_{Borrower}$ (1/0)	0.166*	0.142	0.168	-0.153	-0.368*	-0.333
	(0.067)	(0.101)	(0.112)	(0.371)	(0.075)	(0.100)
Carbon intensity $Q2_{t-1}$	0.955***	0.759***	0.800***	-0.130	0.032	0.097
	(0.006)	(0.001)	(0.001)	(0.630)	(0.890)	(0.679)
Carbon intensity $Q3_{t-1}$	1.096***	0.954***	0.957***	0.229	0.263	0.323
	(0.001)	(0.000)	(0.000)	(0.443)	(0.348)	(0.246)
Carbon intensity $Q4_{t-1}$	1.368***	1.226***	1.246***	0.136	0.614*	0.727**
	(0.000)	(0.000)	(0.000)	(0.660)	(0.073)	(0.043)
Carbon intensity $Q5_{t-1}$	1.378***	1.287***	1.205***	0.486	0.433	1.010***
	(0.000)	(0.000)	(0.000)	(0.184)	(0.345)	(0.008)
Deal-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	No	Yes	Yes	No	Yes	Yes
Country-level controls	No	No	Yes	No	No	Yes
Cohort ×lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,256	918	798	1,282	935	815
Adj. R^2	0.984	0.986	0.986	0.794	0.811	0.823

Notes: Table OAB. VI presents deal-level stacked DID regression estimates of how the effects of a borrower-country carbon tax vary with borrowers' prior-year carbon-intensity quintile. The dependent variable in Columns (1)-(3) is the carbon intensity of the loan, measured as the borrower's annual Scope 1 CO_2 emissions (in metric tons per million US dollars of revenue) at the deal level. The dependent variable in Columns (4)-(6) is the cost of the loan, measured as the natural log of the all-in-spread-drawn of the deal issued by the syndicate's lead arranger in a given year. Panels A and B report results for the full sample and the subsample of foreign loans, respectively. $PostCT_{Borrower}$ equals one from the year the carbon tax is introduced in the borrower's country onward, and zero otherwise. Borrowers are sorted into five quintiles based on prior-year carbon intensity (Q5 is the highest quintile); the omitted category is Q1. Treatment timing and cohort construction follow Table 5. Columns (1) and (4) include borrower and deal-level controls, Columns (2) and (5) add lender characteristics, and Columns (3) and (6) further include country-level controls. All regressions include cohort × lender and cohort × year fixed effects. Standard errors are clustered at the borrower-country level. All models control for the same set of variables as in Table 3 Panel A. The sample period spans from 2002 to 2022. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A2. *P*-values are reported in parentheses. Statistical significance is denoted by *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.