Resistance and Arbitrage: International Trade in Brown Loans

LISHU ZHANG*

I develop a novel measure of carbon sensitivity in lending to assess reductions in portfolio exposure to brown assets. Using syndicated loan data, I show that countries with greater resistance to brown lending, proxied by economic development, experience faster shifts in the sectoral composition of loan portfolios. The decarbonization is driven primarily by domestic credit reallocation. I find consistent evidence of risk transfers to less regulated lenders and foreign countries, indicating arbitrage and incomplete regulations. Furthermore, lenders' climate risk-taking and transfer behaviors vary sharply by syndicate role, loan type, and specialization. The existence of international trade in brown loans has important implications for supervisory evaluation. Using the European Central Bank's climate guide, I show that accounting for regulatory leakage reveals effects contrary to common wisdom.

JEL: G21, G32, Q58, E44, O16
Keywords: International lending, Portfolio decarbonization, Economic development, Climate risk transfers, Supervisory leakage

* Zhang: Department of Economics, CentER, Tilburg University. Email: `l.zhang_3@tilburguniversity.edu`. Personal website: `https://lishuz.github.io/`. I am grateful for the helpful comments from my supervisors, Prof. Harry Huizinga, Prof. Harald Benink and Dr. Louis Raes. I appreciate the comments from Lin Sun (discussant), Guzman Ourens, Dajana Xhani, Shubhdeep Deb, Shuo Zhao, John Bai, Re-Jin Guo, Zihao Liu, Joern Onken, and participants at the AsianFA 2025 annual meeting in Taipei and CICF 2025 in Shenzhen. All errors are mine.

Introduction

Climate change is a global problem that requires international coordination. The most recent UN Climate Change Conference (COP29) spotlighted the role of finance in helping countries combat climate change and further addressed the financial needs of developing countries. The new finance goal to "triple finance to developing countries" requires capitals to move from developed to developing regions, especially to more sustainable sectors such as renewable energy.

Market provision for climate finance is crucial for building global climate resilience. As a major source of credit, banks' potential to support the net-zero transition has only recently gained attention.[1] Climate-related considerations drive changes in bank lending flows between countries. Banks reallocate loans geographically in response to climate-related regulatory changes (Benincasa et al., 2022; Demirgüç-Kunt et al., 2024; Laeven & Popov, 2023). These cross-border credits can help achieve the finance goals by scaling up climate-related investments, but they can also slow down the transition by financing high-emission activities in more vulnerable regions instead. The question of what firms these cross-border loans finance is crucial to uncovering the impact of cross-border banking activities on net-zero transition.

Evaluating aggregate credit allocation provides meaningful insights into the status quo of climate finance through credit extension, serving as a foundation for informed and effective policymaking. In light of the climate finance goals set at COP29, assessing lending flows from more developed countries is particularly important. In this paper, I document several systemic shifts in aggregate loan flows using global syndicated loan data from 2000 to 2023, including a more rapid green transition in the loan portfolios of developed countries and a persistent gap between their domestic and foreign decarbonization progress. A one-standard-deviation increase in GDP per capita is associated with a 0.71 (0.99) reduction in the total (domestic) portfolio weight of a sector that is one standard deviation higher in its emissions intensity, representing 10% (14%) of the pertinent mean sectoral weight.

As a key implication, lenders from less developed countries are becoming the main funding source for high-emission sectors in the global syndicated loan market. Meanwhile, lenders from developed countries may be redirecting financing to high-emission sectors abroad, bypassing domestic decarbonization pressures while remaining exposed to these risks through international lending. This could slow the transition in less developed regions, undermine global climate goals, and increase climate-related financial risks for institutions in developed countries.

Developing effective policies requires a deeper understanding of how banks allocate capital across regions and firms with varying climate impacts and why. This paper highlights the importance of two opposing incentives in shaping loan allocation. On the one hand, banks can lend in a more socially responsible and sustainable way out of longer-term concerns. For example, some banks screen borrowers based on their environmental performance and influence their subsequent performance to mitigate credit and reputa-

[1] For an overview of research on sustainable banking, see, for example, De Haas (2023).

tion risks (Houston & Shan, 2022; Kacperczyk & Peydro, 2021). On the other hand, banks can arbitrage the regulatory differences and provide cheap capital to foreign emitters. For example, some banks increase cross-border fossil fuel lending at a lower interest rate following the introduction of domestic carbon taxes (Laeven & Popov, 2023).

As a starting point for the multiple-level analysis, I propose a theoretical framework to characterize the trade-off between profitability, diversification needs, and climate-related preferences in lending decisions. Building on this, I develop a novel measure, *carbon sensitivity of lending*, to assess portfolio decarbonization. This measure captures the extent by which a lender would differentially lend to less emission-intensive ("green") and emission-intensive ("brown") borrowers.[2] This differential lending can be explained by three factors: lending opportunity difference, return difference, and brown lending resistance, which reflects the overall reluctance to finance emissions. The first two factors incentivize more brown lending, while the last factor counteracts the arbitrage incentives.

In the baseline empirical analysis, I compare the extent of differential lending to green and brown borrowers across countries with varying levels of economic development. Following the loan share approximation method by Blickle et al. (2020), I impute the missing loan shares and construct a comprehensive overview of bilateral sectoral lending flows. I measure the "brownness" of each sector by emission intensity on value added.[3] I further provide micro-level evidence exploiting within-syndicate variations in the reported share retention and firm-level emission intensities based on revenue. Both macro and micro-level evidence suggests that lenders from developed countries are more inclined to reduce their exposure to brown assets in their portfolios. Additional lender-loan-level results reveal significant heterogeneity in lenders' climate preferences and various reasons behind greater climate risk-taking in foreign countries.

Beyond documenting the divergence in financial decarbonization progress between developed and developing countries, I use GDP per capita as a proxy for country-specific resistance to brown lending. The baseline regressions also assess the impact of this resistance on lenders' carbon sensitivity of lending. My empirical observation is in line with the interpretation that lenders from more developed countries encounter greater barriers to engaging in brown lending activities. The finding is robust against including possible omitted variables that underlie brown lending resistance. A decomposing exercise suggests that this impact of high brown lending resistance on the carbon sensitivity of lending stems from a lower propensity for society to be damaged by climate hazards, a better business environment to leverage market investments to transition actions, and more pro-environmental preferences by the populace.

However, high brown lending resistance, interpreted as pro-environmental preferences and climate supervision targeting both domestic and foreign lending behaviors, cannot

[2]In this paper, I use "dirty" or "brown" for carbon-intensive projects and "clean" or "green" for less emitting ones. The two terms are used interchangeably.

[3]There has been a debate about whether levels of emissions or emission intensities are a better measure of the carbon-transition risks. For example, Bolton and Kacperczyk (2021) advocate the use of emission levels while most practitioners and other climate finance studies support emission intensities. I choose to use emission intensity because I follow a portfolio diversification perspective. Emission intensity allows me to separate per-exposure risk prospects from pure scale effects.

explain the slower decarbonization progress in the foreign portfolios of more developed countries. Sluggish progress abroad may arise from higher returns and lending opportunities in foreign carbon-intensive sectors, reflecting lenders' strategic focus on financial priorities. While this pursuit aligns with shareholder interests, it may undermine coordinated global efforts to address the climate challenge.

In addition to geographical reallocation, banks manage climate risks by increasing credit line lending and shortening maturity, accompanied by higher participation of shadow banks (Bruno & Lombini, 2023; Ivanov et al., 2023; Miguel et al., 2024). This paper provides indirect evidence of another potential channel of brown exposure management — loan sales on the secondary market. I find that the response of carbon sensitivity to brown lending resistance is weaker in loans that are more suitable to sell on the secondary market while stronger among lenders who mostly keep their shares on the balance sheets.

How do lead arrangers adjust their share retention in brown loans? Understanding how brown lending resistance affects lead arranging activities is also interesting for policymakers because lead arrangers play the most important role in the syndication (and hence internalization) process of a brown loan. They endorse brown borrowers and distribute the loans, with skin in the game (Sufi, 2007).

The common argument for lead arrangers' share retention is to signal the quality of the loan. The demand discovery problem faced by lead arrangers further complicates their retention decision (Blickle et al., 2020; Bruche et al., 2020). As the main underwriter, the lead arranger often needs to retain the residual demand when the deal is "cold" and not placed in full, i.e., a pipeline risk addressed by Bruche et al. (2020). As strategic decisions by some lenders can indirectly influence the lending behaviors of others, the institutional structure of syndicated loans provides an opportunity to study this neglected transmission of climate-related credit shocks.

Comparing lead arrangers with other underwriting agents helps eliminate the impact of information asymmetry. By examining differences in share retention across loan facilities with varying demand from non-lead lenders, I provide evidence of a "climate pipeline risk". Lead arrangers retain larger shares in brown loans as demand from other lenders decreases. Specifically, there is a significant difference in share retention between credit lines and term loans. As lenders increasingly use credit lines with brown borrowers, lead arrangers face a more severe pipeline risk in term loans.

A key implication is that as some lenders are more able to adjust their exposure to climate risks, these browner assets may concentrate on the portfolios of other lenders. This concentration could heighten the risks faced by individual institutions and become a potential source of financial instability. These results highlight the complex risks financial institutions face during the net-zero transition, suggesting the potential benefits of microprudential climate supervision measures.

An important follow-up question is whether incorporating climate-related measures into financial supervision can guide the green transition while ensuring the financial health of credit institutions. A recent example of climate supervision efforts is the European Central Bank's (*ECB*) publication of the Guide on climate-related and environmental risks for banks (*the Guide*) in November 2020. Leveraging the quasi-exogenous change in perceived supervisory pressure among directly supervised banks, I examine whether such climate supervision helps direct market-based financing to sustainable and climate-positive investments.

The international data allow me to address the concern that lenders within the same supervisory area, even if not directly targeted by the Guide, are unsuitable as a control group due to potential indirect effects. I propose using international lenders who are not subject to European banking supervision as the control group. That is, I consider both significant institutions that are directly targeted by the Guide and other lenders under the same supervisory framework "treated" following the shock of the Guide. I allow the treatment effects to differ for these two groups.

My results suggest that a soft measure with supervisory disparity can backfire. Both directly supervised lenders and other lenders under European banking supervision show a greater tendency to expand brown lending than unrelated international lenders following the publication of the Guide, both domestically and abroad. One explanation for the observed rebounds is that lenders under ECB banking supervision may have prepared for worse before the publication of the guide. The publication of the Guide may have accidentally relieved them from anticipatory anxiety.

I summarize several other notable findings from the paper. First, by examining share retention in foreign loans across different lender roles and loan types, I identify non-lead lenders in credit lines as the main contributors to the observed sluggish foreign financial decarbonization in developed countries.

Second, the direct lending outcomes can also depend on the lending preferences of their parents. To rule out the potential impact of redistribution along the organizational structure, I aggregate the loan shares at the parent lender level and test whether there is a fundamental difference between banks and non-banks. I show that nonbanks and banks with stronger capital positions from developed countries are more likely to behave differently in their domestic and foreign portfolios. This evidence also implies a possible cross-border carbon arbitrage as a result of incomplete supervision, in line with Benincasa et al. (2022).

Third, using Relative Comparative Advantage (RCA) measures, constructed as the weight of a given sector in a lender's portfolio relative to the weight of this sector in the total lending, I also provide direct support for a generic role of sector-specific specialization in driving cross-border brown lending, in line with Benincasa et al. (2022) and Laeven and Popov (2023). However, lending specialization in browner sectors seems to affect associated lending less compared to specialization in other sectors. I interpret this as a sign of increased climate risk management by these lenders with brown-sector specialization, potentially because lenders with excessive brown exposure see the importance of diversification as climate hazards increase.

Related literature. This paper first contributes to the growing literature on sustainable banking. My work confirms and expands the findings on banks' exposure management for climate risks by, for instance, Degryse et al. (2023), Faiella and Natoli (2018), Houston and Shan (2022), Ivanov et al. (2023), Jung et al. (2023), Martini et al. (2023), Meisenzahl (2023), Nguyen et al. (2023), and Reghezza et al. (2022).[4]

Focused on climate-related loan reallocation, my paper is most closely related to Benincasa et al. (2022), Bruno and Lombini (2023), and Laeven and Popov (2023). Laeven and Popov (2023) study how the introduction of carbon taxes in home countries changes the geographical allocation of fossil fuel loans, while Bruno and Lombini (2023) consider the impact of host country engagement. Benincasa et al. (2022) find that loans generally flow from countries with stricter climate policies to those with weaker ones. All three papers provide micro-level evidence of a "relocation" of climate risks where fewer loans are given to domestic brown firms but more to foreign equivalents.

My contributions relative to these papers are as follows. First, I provide the first macro-level documentation of changes in aggregate loan portfolio allocation. These shifts may have far-reaching impacts on industrial development and global financial stability. Second, rather than focusing on cross-country differences in climate policy stringency, I examine the divergence in financial decarbonization progress between countries with varying levels of economic development, which reflects a complex interplay of institutional factors, market forces, and preferences. Third, I relate banks' differential risk-taking to the dynamics of loan syndicates and provide novel evidence on within-syndicate transmission of credit supply shocks.

This paper is also linked to a broader discussion on global capital allocation. Recent studies start incorporating climate risks in explaining, for example, foreign direct investment (Gu & Hale, 2023) and equity holding (Benink et al., 2024). My work adds to this literature by showing how climate considerations have also structurally impacted banking flows.

Furthermore, my work contributes to the discussion on climate banking supervision. In terms of rule-based climate banking supervision, Fan et al. (2021) confirm the credit reallocation effects of China's substantially strengthened enforcement of green credit regulations in 2012. Similarly, Miguel et al. (2024) find effects of embedding climate risks into large Brazilian banks' risk management frameworks, with treated banks reallocating their lending away from exposed sectors. Both papers suggest some unintended effects, such as causing small firms to scale down production and brown credit expansion through unaffected banks. In line with Miguel et al. (2024), I show the unintended consequence of the ECB's guide on those lenders who are not directly targeted. My paper reveals a potential negative effect of a common climate supervisory measure — supervisory expectations.

Exploiting the same regulatory change with intra-European loans, Aiello (2024) finds some evidence of credit allocation away from polluting firms and mixed evidence concerning polluting firms with commitments to future improvement. My work differs from Aiello (2024) by proposing a different control group. My results show that using those non-targeted lenders from the same supervisory area as a control group can lead to an opposite conclusion. Faster brown credit expansion among the "unintended" group leads

[4] A larger literature in this field has studied climate pricing, including Bae et al. (2018), Chava (2014), Degryse et al. (2023), Delis et al. (2024), Ehlers et al. (2022), Goss and Roberts (2011), Ho and Wong (2023), and Javadi and Masum (2021).

to a "false" drop in brown lending by directly supervised banks, which also implies a direct consequence of unequal supervision.

Regulatory leakages have been widely documented by, for example, Aiyar et al. (2014) regarding capital regulations in the UK and Buchak et al. (2018) and Irani et al. (2021) on the rise of fintech and shadow banks. My finding additionally contributes to this broader discussion on financial regulation, calling for more discernment in policymaking.

The paper proceeds as follows. Section I introduces the theoretical framework and derives the theory-based empirical strategy. Section II describes the data, variables, and samples. Then, I present a macro-level analysis in Section III and a micro-level analysis in Section IV. In Section V, I discuss the two important drivers of risk transfers, lenders' brown specialization and supervisory changes. Finally, Section VI concludes.

I. Theoretical framework

A. International lending flows

I follow the framework from Aviat and Coeurdacier (2007) and characterize a two-country case. The baseline model assumes an exogenous number of projects in each country and homogeneous prices within each country.

Households. There are n_i identical households in each country i, $i \in \{1,2\}$. At $T = 1$, each household h in country i is endowed with a wealth of y_i in the equity of its domestic bank and a risky project that seeks funding from banks. The total mass of each project is normalized to one. At $T = 2$, the households consume using the retained net returns from the projects as well as the profits of the bank as its shareholder.

Bank. Each lending (or source) country i has a representative risk-averse bank l_i that manages its assets by financing the projects. A bank can lend to both domestic and foreign projects to make a lending portfolio. The representative bank in country i pays $p_{ij} = p_j \tau_{ij}$ for financing a share in a project from the borrowing (or destination) country j, where p_j is the price for a share in any project from country j, and τ_{ij} is an iceberg transaction cost with $\tau_{ij} > 1$ for $i \neq j$ and $\tau_{ii} = 1$.

Project type. I introduce the climate risk into this model following Oehmke and Opp (2022) by imposing an exogenous supply of clean and dirty assets. Each project is assumed to be one of two observable types, $q \in \{C, D\}$, referring to clean and dirty. For each country i, the population fraction of type-C (type-D) projects is given by π_i ($(1-\pi_i)$).

Brown lending resistance. Climate-related risks affect risk perception of dirty projects disproportionately. I assume banks incur an extra cost for granting a brown loan. This cost is referred to as brown lending resistance.[5]

[5]The cost is in pecuniary terms, which can arise from the pro-environmental preference of the representative bank or that of its domestic supervisor. If brown lending resistance arises from the societal preference of the bank, θ can be understood as, for example, an ex-post cost of carbon offset. If brown lending resistance arises from the supervisory preference, θ can be, for example, a regulatory penalty.

I define a parameter θ_i to measure this brown lending resistance. The representative bank from country i expects to eventually receive a fraction θ_i of the ex-ante brown return d_{D_j} per share of brown lending to the type-D projects in country j. The larger the brown lending resistance is, the smaller θ_i would be. In this framework, this parameter induces asymmetric allocation changes across countries.

Need for diversification. Following Aviat and Coeurdacier (2007), the environment is stochastic with L equally likely states of nature at $T = 2$. The total number of projects is $M = n_1 + n_2$, of which $M_C = \pi_1 n_1 + \pi_2 n_2$ are clean and $M_D = (1-\pi_1)n_1 + (1-\pi_2)n_2$ are dirty. The markets are incomplete with $M = L-1$, which characterizes imperfect substitution between assets. This combination of stochastic realization and an incomplete market gives rise to a diversified portfolio.

A project in destination country j run by household h pays off d_{qj} only when the project's state h_j matches the realized state of nature m. After considering the cost of brown lending, each project from country j has a payoff per share to the representative bank of country i as below:

$$\begin{cases} 0 & \text{if } h_j \neq m \\ d_{C_j} & \text{if } h_j = m \text{ and } q = C \end{cases} \quad \text{or} \quad \begin{cases} 0 & \text{if } h_j \neq m \\ d_{D_j}\theta_i & \text{if } h_j = m \text{ and } q = D \end{cases}$$

Baseline problem. Different projects are imperfect substitutes for banks with constant elasticity of substitution $\sigma > 1$. The combination of stochastic realization and an incomplete market gives rise to a well-diversified portfolio in the sense that banks would finance a little of every project to hedge against the uncertainty of future realization. The optimization problem is symmetric for the two representative banks under their individual budgets and banking regulations. To simplify, I assume there is a static country-specific reserve requirement, which mandates a minimal share s_i of total capital to rest. The capital set aside has no returns, while the risky investments have a positive expected return. So banks always put in reserves only to the minimum level required.

I refer to the country with higher endowment level y as Country 1 (and domestic country) and the other country as Country 2 (and foreign country). Denote the share by the representative bank of country i (hereafter Bank i) in Project h from country j with x_{ij}^h. Bank 1 chooses $\{x_{11}^h\}_{h\in\{1,\ldots,n_1\}}$, domestic loan shares, and $\{x_{12}^k\}_{k\in\{1,\ldots,n_2\}}$, foreign loan shares, under the minimum reserve requirement s_1. Formally, Bank 1 maximizes its utility as follows:

$$\begin{aligned} &\max_{\{\{x_{11}\},\{x_{12}\}\}} \left\{ \mathbf{E}\left(\frac{D_1^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \right) \right\} \\ &\text{s.t.} \quad \sum_{k=1}^{n_2} p_2 \tau x_{12}^k + \sum_{h=1}^{n_1} p_1 x_{11}^h \leq n_1 y_1 (1-s_1) \end{aligned} \tag{1}$$

where D_1 indicates the returns of Bank 1, and τ is a simplification of τ_{12}.

The share choices are made based on the prices and returns of each project. The within-country price homogeneity and return differences (across countries and types) group projects into domestic-clean, domestic-dirty, foreign-clean, and foreign-dirty projects. Within each group, the prices and returns are identical. The optimization problem boils down to choosing four shares. That is, $\{x_{12}^k\} = x_{12}^C$ for all foreign clean projects and $\{x_{12}^k\} = x_{12}^D$ for all foreign dirty projects, and $\{x_{11}^h\} = x_{11}^C$ for all domestic clean projects and $\{x_{11}^h\} = x_{11}^D$ for all domestic dirty projects.

To solve the problem, I derive the first order conditions with respect to x_{11}^C, x_{12}^C, x_{11}^D and x_{12}^D to obtain the optimal per-project shares given a Lagrange multiplier. I then use the binding budget constraint to solve for the Lagrangian multiplier.[6]

Denote the expected net returns: $R_1^C = \frac{d_1^C}{Lp_1}$, $R_2^C = \frac{d_2^C}{Lp_2}$, $R_1^D = \frac{d_1^D}{Lp_1}$ and $R_2^D = \frac{d_2^D}{Lp_2}$. Index the aggregate return of Country 1's portfolio with $\mathbf{R_1} = \frac{\pi_1 n_1}{L}(R_1^C)^{\sigma-1} + \frac{\pi_2 n_2}{L}(\frac{R_2^C}{\tau})^{\sigma-1} + \frac{(1-\pi_1)n_1}{L}(\theta_1 R_1^D)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(\frac{\theta_1 R_2^D}{\tau})^{\sigma-1}$. Country 1's aggregate lending to domestic-clean ($\mathbf{X}_{11}^C$), domestic-dirty ($\mathbf{X}_{11}^D$), foreign-clean ($\mathbf{X}_{12}^C$), and foreign-dirty ($\mathbf{X}_{12}^D$) projects are given by:

$$
\begin{aligned}
\mathbf{X}_{11}^C &= \frac{\pi_1 n_1}{L}\,(1-s_1)n_1 y_1\,\frac{(R_1^C)^{\sigma-1}}{\mathbf{R_1}},\\
\mathbf{X}_{11}^D &= \frac{(1-\pi_1)n_1}{L}\,(1-s_1)n_1 y_1\,\frac{(R_1^D\theta_1)^{\sigma-1}}{\mathbf{R_1}},\\
\mathbf{X}_{12}^C &= \frac{\pi_2 n_2}{L}\,(1-s_1)n_1 y_1\,\frac{(R_2^C/\tau)^{\sigma-1}}{\mathbf{R_1}},\\
\mathbf{X}_{12}^D &= \frac{(1-\pi_2)n_2}{L}\,(1-s_1)n_1 y_1\,\frac{(R_2^D\theta_1/\tau)^{\sigma-1}}{\mathbf{R_1}}.
\end{aligned}
\tag{2}
$$

Bank 2 faces a symmetric problem, and thus its lending flows can be obtained likewise.

The type-specific domestic and bilateral lending flows follow a general gravity form, including a financing demand factor capturing the size of each project type in the destination country, such as $\pi_2 n_2$ in $\mathbf{X}_{12}^C$, a supply factor capturing the available capital, e.g., $n_1 y_1$, a return factor, e.g., $R_2^{C\,\sigma-1}/\mathbf{R_1}$ and lastly the frictions, e.g., $\tau^{\sigma-1}$. For brown lending $\mathbf{X}_{11}^D$ and $\mathbf{X}_{12}^D$, there is a brown lending resistance term ${\theta_1}^{\sigma-1}$, specific to the lending country.

Comparative results. I compare the capital flows towards the two types of projects in relative terms for each market.

Definition 1. *The carbon sensitivity of lending measures the extent to which a bank allocates more capital toward clean projects than to dirty projects. Formally, carbon sensitivity of lending equals* $\log(\mathbf{X}^C) - \log(\mathbf{X}^D)$.

[6] The details are provided in Appendix A.

Lemma 1. *The bilateral carbon sensitivity of lending can be written as a sum of three components: the relative share between the two types of projects, the relative expected net return between the two types of projects in the pertinent market, and brown lending resistance. Formally,*

$$log(\frac{X_{ij}^C}{X_{ij}^D}) = log(\frac{\pi_j}{1-\pi_j}) + (\sigma-1)(logR_j^C - logR_j^D) - (\sigma-1)log\theta_i,$$

where i indexes the home (or source) country and j the host (or destination) country. The same equation holds for the ratio of weights.

A similar equation holds when comparing the aggregate allocation of capital between clean and dirty projects, but the relative return term will be more complicated. The relative fraction represents the relative loan demand (lending opportunities) from the two types of projects. Moreover, following the incomplete market assumption, they also capture the need for insurance against different states of the world.

The following propositions hold for a country with access to the international market of loans.

Proposition 1. *If brown lending resistance increases in a country (represented by a smaller θ), ceteris paribus, the country will*

1) lend more to both domestic and foreign clean projects, resulting in a greater aggregate clean lending flow;
2) lend less to both domestic and foreign dirty projects, resulting in a smaller aggregate dirty lending flow;
3) have a higher carbon sensitivity of lending in both domestic and foreign markets.

On the other hand, it does not affect the lending decisions of foreign countries.

Given R^H and $\sigma > 1$, the carbon sensitivity of lending on total, domestic, and foreign portfolios all increases as θ decreases. This also holds when comparing two otherwise identical countries with different θs.[7]

Lemma 2. *A country-specific brown lending resistance that targets all lending activities should symmetrically impact this country's domestic and foreign portfolios.*

This lemma considers how much $\frac{W_{11}^C}{W_{11}^D}$ and $\frac{W_{12}^C}{W_{12}^D}$ are affected by θ_1, whereby the lenders face the same brown lending resistance force in their domestic and foreign lending. Although the relative prices of clean and dirty projects differ on the domestic and foreign markets due to the financial friction τ, the extent to which θ shifts the level of carbon sensitivity of lending is the same for these two portfolios. In other words, a country-specific climate measure targeting all lenders and incomes from all destinations presents no room for international arbitrage.

[7]In general, the relative carbon sensitivity of lending between two countries depends on three factors: the relative green loan demand, the relative green premium, and the relative brown lending resistance. A higher share of green firms, and/or a higher relative return from green loans, and/or higher brown lending resistance leads to a larger carbon sensitivity of lending.

Lemma 3. *A difference in the levels of carbon sensitivity of lending on two different markets is driven by:*

1) *a difference in the relative shares of clean projects to dirty projects between the two markets,*
2) *a difference in the relative return of clean projects over dirty projects between the two markets.*

The brown lending resistance affects each market-specific portfolio equally, as Lemma 2 states. However, a country's carbon sensitivity of lending can still differ across markets due to the differences in the shares of available clean projects and in the relative returns. A country has a larger carbon sensitivity of lending in a market with more clean lending opportunities and higher green returns (or lower brown returns).

Proposition 2. *If a country's domestic climate policy reduces the domestic dirty return R_1^D, ceteris paribus, the country will*

1) *lend more to both domestic and foreign clean projects, resulting in a greater aggregate clean lending flow;*
2) *lend less to domestic dirty projects but more to foreign dirty projects, resulting in a smaller aggregate dirty lending flow;*
3) *have a higher carbon sensitivity of lending in the domestic market only.*

In the meantime, the foreign country will

1) *lend more to both domestic and foreign clean projects, resulting in a greater aggregate clean lending flow;*
2) *lend more to domestic dirty projects but less to foreign dirty projects, resulting in a smaller aggregate dirty lending flow;*
3) *have a higher carbon sensitivity of lending in the foreign market only.*

Proposition 3. *Consider the case where brown lending resistance reduces the ex-post brown returns but a carbon premium persists. If a country's domestic climate policy increases the domestic green loan demand π (reduces the dirty share $1-\pi$), ceteris paribus, the country will*

1) *lend more to both domestic and foreign clean projects, resulting in a greater aggregate clean lending flow,*
2) *lend less to domestic dirty projects but more to foreign dirty projects;*
3) *have a greater total dirty lending only if the ex-post carbon premium is large enough, i.e., $\theta_1 R_1^D - R_1^C > \frac{(R_1^D\theta_1)^{\sigma-1}\mathbf{R}_1}{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_1)^{\sigma-1}+\frac{(1-\pi_2)n_2}{L}(\frac{R_2^D\theta_1}{\tau})^{\sigma-1}}$, and a smaller total dirty lending otherwise;*
4) *have a higher carbon sensitivity of lending in the domestic market only.*

In the meantime, the foreign country will

1) *lend more to both domestic and foreign clean projects, resulting in a greater aggregate clean lending flow,*
2) *lend less to foreign dirty projects but more to domestic dirty projects;*

3) *have a greater total dirty lending only if the ex-post carbon premium is large enough, i.e.,* $\theta_1 R_1^D - R_1^C > \frac{(R_1^D\theta_2)^{\sigma-1}\mathbf{R}_2}{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_2)^{\sigma-1}+\frac{(1-\pi_2)n_2}{L}(\frac{R_2^D\theta_2}{\tau})^{\sigma-1}}$*, and a smaller total dirty lending otherwise;*

4) *have a higher carbon sensitivity of lending in the foreign market only.*

B. *Multi-type extension and empirical model*

The baseline model considers two broad types of projects. To extend Equation 2 to incorporate more types of assets with varying levels of climate risks, I consider more types of projects with different levels of "dirtiness", indexed with K in descending order of carbon productivity, i.e., the economic value provided by one more unit of emission. A larger index would refer to a dirtier project. Each project type K from country j has its own return R_{Kj}. Moreover, the impact of climate risks on the expected return is now both type-specific and country-specific, i.e., $\theta_K^i \in (0,1]$. For a given country i, θ_K^i decreases in K. The multi-type version of the bilateral gravity equation can be written as:

$$X_{i,j,K} = \frac{\pi_K}{L}\frac{n_i y_i n_j}{\tau_{ij}^{\sigma-1}} \times \frac{R_{K,j}^{\sigma-1}}{\mathbf{R_H}} \times \theta_K^{i\,(\sigma-1)}.$$

which can flexibly account for the intermediate project types. Here, i indicates the origin or lending country, j the destination or borrowing country, and K the asset type.

I derive the empirical model in two steps. In the first step, I specify $\theta_K^i = \theta_i^{\eta_K}$. The country-specific θ_i reflects country-specific brown lending resistance, represented by a cost for financing a unit of emission. The η_K measures the extent to which such costs may be applied to projects of type K compared to the cleanest benchmark $\eta_0 = 0$. And η_K is increasing in K. The gravity equation then becomes:

$$X_{i,j,K} = \frac{\pi_K}{L}\frac{n_i y_i n_j}{\tau_{ij}^{\sigma-1}} \times \frac{R_{K,j}^{\sigma-1}}{\mathbf{R_H}} \times \theta_i^{\eta_K(\sigma-1)},$$

which can flexibly account for the intermediate project types. The panel equivalence is as follows:

$$\begin{aligned} X_{i,j,t}^{K} =& Exp\,\{\alpha + \log(n_{it}y_{it}) + \log(n_{jt}) - (\sigma-1)\log\tau_{ij} + \log(\pi_{Kt}) \\ &+ (\sigma-1)\log(R_{K,j,t}) + (\sigma-1)\eta_{Kt} \times \log(\theta_{it})\}\ \varepsilon_{ijt} \end{aligned}$$

In the second step, I hypothesize that economic development is the key determinant of the country-specific brown lending resistance. In the empirical part, I quantify $\log(\theta)$ using log(GDP per capita).

I expect countries with higher economic development to show stronger resistance to brown lending, resulting in lower θ. In the robustness checks, I also include other potential factors that could impact θ through channels that are not captured by economic development.

I use $\frac{\partial\ \log(X^i_{K_j})}{\partial\eta_K}$ to empirically measure the extent to which a country lends more towards dirty projects, i.e. the negation of carbon sensitivity of lending. It can be written as:

$$\frac{\partial\ \log(X^i_{K_j})}{\partial\eta_K} = \frac{\partial\log\pi_{Kj}}{\partial\eta_K} + (\sigma-1)\frac{\partial\log R_{Kt}}{\partial\eta_K} + (\sigma-1)\log\theta_i.$$

To construct an empirical identification equation, observe that $\frac{\partial\ \log(X^i_{K_j})}{\partial\eta_K}$ is only correlated with the components with a subscript K as well as θ_i. Since π_{Kj} and R_{Kj} are not correlated with the characteristics of the lending country, the identification equivalence is given by:

$$\frac{\partial\ \log(X^i_{K_j})/\partial\eta_K}{\partial\log(\text{GDP per capita}_i)} = (\sigma-1)\frac{\partial\log\theta_i}{\partial\log(\text{GDP per capita})_i} = \mu(\sigma-1), \tag{3}$$

where μ represents the quantitative relationship between $\log(\text{GDP per capita})$ and $\log\theta$.

I use emission intensity (hereafter EI_{Kt}) as a proxy for η_{Kt}. I then include a rich set of fixed effects to absorb all other factors except the interaction term. This then gives the baseline gravity equation to estimate:

$$X^K_{i,j,t} = Exp\left[\alpha + \beta EI_{Kt-1}\times\log(\text{GDP per capita})_{it-1} + \lambda_{ij} + \lambda_{it} + \lambda_{Kjt}\right]\varepsilon_{ijt} \tag{4}$$

where i indicates the origin or lending country, j the destination or borrowing country, K the sector and t year. $\lambda_{ij}, \lambda_{it}$ and λ_{Kjt} represent the country-pair, origin country $\times$ year and project type $\times$ destination country $\times$ year fixed effects respectively. The coefficient β of the interaction term $EI\times\log(\text{GDP per capita})$ measures the change in the relative allocation between two assets with a unit difference in their "dirtiness" as GDP per capita increases. The main variables are lagged by one year to mitigate the endogeneity issue.

Hypothesis. *A country with a higher economic development will lend less to dirty projects and have a larger carbon sensitivity of lending. That is, β is negative.*

The international disparity in brown lending resistance leads to diverging changes in countries' portfolio composition. This implies that, in reality, brown lending can be transferred from countries with high resistance to countries with low resistance via the international market.

In reality, lending returns cannot be exogenous and static. The step to obtain Equation 3 requires that economic development should not change the carbon premium $\log R_{Kt}/\partial\eta_K$ and the loan demand structure $\log\pi_{Kj}/\partial\eta_K$. This holds automatically in foreign lending (when $i\neq j$) as the carbon premium and demand structure in another country should be determined by that country's fundamental characteristics. However, in the case of domestic lending, the estimate β might be contaminated by other effects.

To the best of my knowledge, there is no empirical evidence on either of the two channels discussed above in the context of bank lending. The closest literature is Bolton and Kacperczyk (2023) and Ginglinger and Moreau (2023). Bolton and Kacperczyk

(2023) find that countries' overall economic development does not seem to be related to stock carbon premium.[8] Ginglinger and Moreau (2023) suggests that brown firms reduce their demand for debt without examining how this tendency is related to economic development.[9] If economic development decreases the carbon premium in loan markets and/or aggregate loan demand from the domestic brown sector, I expect the countries with higher economic development to show an even larger increase in their domestic carbon sensitivity of lending.

I estimate the baseline gravity specification with bilateral international lending flows as well as the weights of each type of asset with respect to the full, domestic, and foreign portfolios. I then extend the analysis to a more granular level, using the bank's sectoral exposure as well as lending shares in each loan facility.

In the empirical context, the coefficient β from the nonlinear specifications based on Equation 4 measures how the semi-elasticity of lending with regard to emission intensity changes as income per capita rises. As this cannot be interpreted as level changes in lending, I facilitate interpretation by using level variables in linear regression for the subsequent tests.

II. Data, variables, and statistics

This section summarizes the data sources and constructed variables used in the empirical analysis.[10] I then describe the constructed samples at multiple levels.

A. *Syndicated loan data*

I exploit the syndicated loan market to address the international credit allocation problem. A syndicated loan is a large loan co-provided by a group of lenders to a single borrower. This syndication of lenders, mainly banks, offers opportunities for geographical diversification (Simons, 1993), risk-sharing (Ivashina & Scharfstein, 2010), information-sharing and monitoring cost-efficiency (Sufi, 2007).

There are several advantages of using syndicated loan data. First, the syndicated loan market is highly international. Syndicates formed by global lenders provide the spatial variations needed for trade-like patterns. Second, this market matches the model setup. The syndication process embodies the portfolio choices made by lenders. Firms borrowing in this market often demand large loans, and each lender determines how much to contribute to each facility. The borrowing firms also have diverse backgrounds with sufficient variations in terms of climate risk relevance. Lastly, the syndicated loan data have good coverage and are commonly used in the literature.

I obtain extensive syndicated loan data from LPC DealScan for the years from 2000 to 2023. Among the rich set of variables available, I mainly use, on the lender side, the loan

[8]Bolton and Kacperczyk (2021) show that differences in economic development levels do not appear to explain much of the variation in long-run carbon premiums across countries. However, there is some weak evidence that firms in countries with higher GDP per capita have smaller short-term carbon premiums in stock markets.

[9]In a broader context, Babiker (2005) suggest that the green policies in the industrialized countries can cause significant relocation of energy-intensive industries away from these countries. This relocation may cause the demand for brown loans to further diverge between more developed countries and the others.

[10]I provide a full list of variables in Table C1 with descriptions and sources.

shares of the lenders, their roles and nationalities, and tranche characteristics, and on the borrower side, the borrowers' nationalities and industries. I consider each loan facility ("tranche") as a unit of loans to account for loan package heterogeneity.

Lender shares. LPC DealScan provides lender shares at the time of loan origination, but such data are available only for 21.8% of the total observations. This selective availability is not a concern when I compare the lenders' contributions in the same loan facility. However, for the country-level analysis, the missing shares are an obstacle for the accounting exercise in constructing bilateral lending flows as well as aggregate lending portfolios.

Another issue is that loan shares reported during the origination may not precisely measure actual lending flows. Syndicated loans are traded on the secondary market. Blickle et al. (2020) detect frequent and sizeable selloffs that take place only days after origination. They propose a method to estimate post-origination loan ownership using the loan facility and lender characteristics.

The approximation method proposed by Blickle et al. (2020) is based on the empirical relationship between post-origination holdings and reported shares from mapping US regulatory fillings (the Shared National Credit) to the LPC DealScan data. Assuming this relationship also holds for non-US lenders to a reasonable extent, I apply the method to the full sample. This approximation mitigates the threats posed by incomplete share reporting and immediate selloff to my international lending accounting exercise. After approximation, the coverage of total observations with lender shares increases to 99.7% of bank lender observations and 97.8% of all observations.

Despite the merits of the predicted shares, they are not suitable for firm-level tests involving heterogeneity, as loan type and lender roles are exploited in the approximation procedure. Therefore, I mainly use reported shares for the micro-level analysis.

It is worth noting that these two measures not only provide alternative measurements for the lending flows but also capture the initial commitment vis-à-vis the (approximated) retained commitment on the balance sheet. Their difference could reflect a potential selloff right after origination.

COUNTRY-LEVEL LENDING FLOWS

Based on the *approximated* shares, I construct the country-level measures.

Bilateral lending — the sector-specific bilateral syndicated loan flows between two countries in a year:

$$X_{ijt}^{K} = \sum_{l \in L_i} \sum_{b \in B_{jK}} \text{approximated share}_{lbt} \times \text{loan amount}_{bt}$$

where K indicates the sector, l and b index the lender and loan respectively, and t indexes the year. L_i is the set of lenders from country i (based on parent nationality), B_{jK} is the set of loans with borrowers from sector K in country j.

Sectoral weight — the value weight of sectoral loans in a country's aggregate lending portfolios. Specifically,

$$\text{Sectoral weight in total portfolio:} \quad \frac{\sum_j X_{ijt}^K}{\sum_K \sum_j X_{ijt}^K} \times 100\%$$

$$\text{Sectoral weight in domestic portfolio:} \quad \frac{\sum_{j=i} X_{ijt}^K}{\sum_K \sum_{j=i} X_{ijt}^K} \times 100\%$$

$$\text{Sectoral weight in foreign portfolio:} \quad \frac{\sum_{j\neq i} X_{ijt}^K}{\sum_K \sum_{j\neq i} X_{ijt}^K} \times 100\%$$

LENDER-LEVEL SECTORAL EXPOSURES

I construct the yearly portfolios at the direct lender level based on the reported shares.

Reported sectoral loans — total values of lending by a direct lender to each sector, computed on the reported shares.

LOAN-LEVEL LENDING SHARES

Based on the *reported* shares, I construct the loan-level lending measures. The loan facilities with more than 100% shares reported are excluded from the sample.

Share in a loan facility (%) — the reported loan share of each direct lender in a loan facility, measured as a percentage.

Total share in a loan facility (%) — the sum of the reported loan shares of direct lenders with the same parent lender in a loan facility, measured as a percentage.

OTHER VARIABLES

Lender roles. Loan syndication is a process with complicated interactions between lenders and the borrower.[11] To start, a borrowing firm decides on the lead arranger from the banks that show interest after their screening. Then the contracting follows, where the lead arranger (and sometimes co-agents) and borrower agree on the arrangement fees and preliminary loan terms. Next, the lead arranger and co-agents (typically book runners) start "syndicating" the deal to secure the necessary funds for the borrower. To market the deal, agents need to acquire information about the borrower, negotiate loan terms, and provide administrative services (Dennis & Mullineaux, 2000; Simons, 1993). Once a deal receives sufficient interest and commitments under agreed terms, the final contract is signed.

I distinguish between the underwriting-related agents and mere loan suppliers using two slightly different divisions. First, I identify a broader set of agents that are involved in the underwriting process following a similar approach to Blickle et al. (2020) and Sufi (2007). I label all these lead arranger candidates identified by their approach as

[11] See Blickle et al. (2020) and Bruche et al. (2020) for a more detailed description of the entire process.

"Agent".[12] Then I determine the lead arrangers following Chakraborty et al. (2018). This approach is consistent with Blickle et al. (2020) and Sufi (2007) but can identify lead arrangers for more loan facilities.

Tranche types. A tranche is a loan package with agreed loan terms. Lenders can tranche a deal to fit different needs and conditions. I follow Blickle et al. (2020) and group the tranches into the following main types: Term A, Term B, unspecified term loans, credit lines, and others. Among the different term loans, Term A refers to amortizing term loans and is more often retained by banks in their balance sheets. Term B, where B stands for bullet or non-amortizing, is more likely funded by or sold to institutional investors (Demiroglu & James, 2015; Haselmann & Wachtel, 2011; Ivashina & Sun, 2011; Nadauld & Weisbach, 2012). Due to the limited observations for Term A and Term B loans, I also combine all types of term loans and refer to the aggregate as term loans.

Relative Comparative Advantage (RCA) measures. I measure the bank sectoral specialization by dividing the weight of a sector in the given bank's portfolio by that in the world portfolio, in line with Giometti et al. (2024) and Paravisini et al. (2023). To be specific, I compute RCA as follows:

$$RCA_{K,b,t} = \frac{s^K_{b,t}}{s^K_t} \quad \text{with } s^K_{b,t} = \frac{lending^K_{b,t}}{\sum_K lending^K_{b,t}}, \text{ and } s^K_t = \frac{lending^K_t}{\sum_K lending^K_t},$$

where $s^K_{b,t}$ stands for the lending weight of sector K in bank b's portfolio in year t, and s^K_t for the weight of sector K in the total portfolio in year t. To mitigate the exposure bias from some particularly large deals and smooth out the measure to better represent lender characteristics, I use a window of three years prior to the given year when computing the weights. Moreover, I compute the RCA on the parent lender level.

To deal with the spare share availability in the LPC Dealscan, Giometti et al. (2024) attribute all the shares to the lead arrangers. To keep the cross-sectional variations, I construct two measures of RCAs using the approximated shares and the reported shares, respectively.

B. *Emission intensity data*

As a proxy for the climate risk relevance of the borrowing firms, two types of emission intensity (EI) measures are employed complementarily, one classifying the firms according to their industry (***EI***) and the other quantifying the individual firm's emission intensity (***EIR*** for distinction).

EI — Emission intensity based on value added. I use the UK statistics of emission intensity by industry as the first proxy for the climate risk relevance of each type of project. The GHG intensity is computed based on the gross value added and maintained yearly.

[12]These "Agents" consist of "Admin agent", "Agent", "Bookrunner", "Joint arranger", "Lead bank", "Lead manager", "Mandated lead arranger", "Co-agent", "Co-arranger", "Collateral agent", "Coordinating arranger", "Documentation agent", "Managing agent", and "Syndications agent".

The GHG intensity data are reported under the UK Standard Industrial Classification of Economic Activities (UK SIC 2007). I manually match the UK SIC codes with the US Standard Industrial Classification used in the DealScan.[13]

One important assumption for the empirical identification using Equation 4 to hold is that the type measurement η_K is independent of the country characteristics. Using the country-specific EI measures and considering the same sector from different countries to be different types would violate this assumption. On the other hand, using one country's EI measures for all countries requires that the relative carbon productivity across industries be sufficiently similar across all other countries.

To signal the validity of this assumption, I compare sectoral rankings across countries using the Energy and Emissions per Value Added Database from the International Energy Agency (IEA). The IEA data only have limited coverage at the sector level and thus are not suitable as an EI proxy for this study.[14]

Specifically, I compare the relative ranking of the emission intensities of four sectors (Mining and quarrying, Manufacturing, Construction, Agriculture, forestry, and fishing) between the UK and twelve other countries (including Austria, Belgium, Croatia, Hungary, France, Germany, Canada, Ireland, Spain, Sweden, the United States, and Mexico) for the year of 2015. The comparison result indicates an overall consistent ranking of sectors' emission intensities internationally, with 10 out of the 12 countries having the same ranking as the UK.[15]

EIR — Emission intensity based on revenue. The micro-level emission intensity measure is computed by dividing the sum of scope 1 and 2 emissions by the revenue of the firm, winsorized at the 1^{st} and 99^{th} percentiles. The scope 1 and 2 emissions are sourced from the Refinitiv Workspace and the CDP database and combined.[16] The revenue data are from the Refinitiv Workspace.

The firm-level EIR is available for roughly 15% of the total observations at the loan-lender level, while the sectoral EI is available for 99% of the observations. The advantage of using the EIR is that it is measured granularly. The heterogeneity in carbon risks of the borrowers can be better captured, providing more variations for identification.

[13]The dataset originally covers 20 sectors and 111 industries. The industry-level sorting is not good enough across countries. One probable reason is that industry fragmentation differs greatly between the US and UK systems, and the granular matching is flawed. I use the sectoral EI of 19 out of the 20 sectors. The sector "Services of households as employers of domestic personnel" is dropped because it is different from the others by its nature.

[14]IEA has an Energy and Emissions per Value Added Database that has sometimes been used in the literature. For the main countries, IEA has data on only 4 to 5 out of 20 main sectors, while the UK data has better coverage. The best time series IEA provides in their database are that of the US and Romania, covering 16 divisions from 5 sectors and 21 years, while the UK statistics cover 20 sectors and all years of my sample span.

[15]I consider the case of 2015 because it gives the best data coverage. The emission intensity of the Manufacturing sector is the value-weighted average of the emission intensity of all the divisions with the necessary data available. Only two countries deviate, Canada and Belgium, with the pertinent emission intensity values only slightly different compared to the sectors ranked below or above.

[16]The borrowers are matched to the two different databases using the Refinitiv permanent identifier (PermID, available from the DealScan) and/or ISIN codes (either reported by the DealScan or obtained via PermID from the Refinitiv Workspace) and/or company names. The matching is examined through cross-validation and some manual checks.

C. Other data

The other data pertain to country characteristics, lender characteristics, and the supervisory status under the ECB's Single Supervisory Mechanism (SSM).

GDP per capita and other country characteristics. The country characteristics data are obtained mainly from the World Bank, supplemented by some national statistics.

Notre Dame - Global Adaptation Index (ND-GAIN). I supplement the country characteristics with the ND-GAIN indexes, consisting of an index of how vulnerable countries are to climate hazards (***Vulnerability***), an index of how capable countries are to leverage investments for climate actions (***Readiness***), and a compound index combining the two aspects (***GAIN***). These indexes are widely used for international comparison of climate efforts, including, for instance, Dechezleprêtre et al. (2022) and Gu and Hale (2023).

Lender characteristics. I supplement the samples with the lender data from the Orbis database. I map the LPC lenders to the Orbis database using lender names and country information. The variables obtained from Orbis on the direct and parent lenders include the type of entity and capital ratios. Based on the type of entity, I divide the lenders into ***Banks*** versus ***Non-bank*** lenders. I then classify lenders with a Tier 1 ratio in the smallest 25^{th} percentiles as ***Weak*** lenders, with the rest being ***Non-weak***.

SSM Supervisory Variables. The SSM entered into force at the end of 2014. Under this supervisory framework, the ECB classifies credit institutions into significant institutions (SI) based on size, economic importance, cross-border activities, and public financial assistance needs, or less significant institutions (LSI) if they do not meet significance criteria.[17] I collect the lists of supervised entities from the ECB website, which have been maintained regularly since the start of 2015.[18]

On November 27, 2020, the ECB published the final guide on climate-related and environmental risks (hereafter *C&E risks*) for banks, formalizing its EU-wide supervisory expectations for banks to inspect and manage their climate-related risks internally. I provide relevant details and a timeline in Appendix B. Although the guide does not impose any binding ratio requirements, it exerts supervisory pressures on brown lending activities. More importantly, only SIs are directly supervised by the ECB, and this supervisory review started to include SIs' performance on C&E risk management.

Based on the regulatory lists of SIs and LSIs, I construct the indicator variables *SI* for a (parent) lending institution if it is listed as an SI during a given year.

[17]Financial institutions outside SSM regions fall outside of the SSM scope. However, among those operating in the SSM region, some still can be neither SIs nor LSIs. For example, institutions such as some credit unions, non-banking financial institutions, and investment firms are not considered credit institutions and thus excluded from the SSM regulation. Moreover, in some cases, branches of non-EU banks may have limited deposit-taking activities and thus do not belong to either SIs or LSIs, and the same applies to even small cooperative banks in some countries.

[18]I map the supervised entities to the Orbis database using the legal entity identifier and monetary financial institutions codes when available and names before these codes were made available. I then add the supervisory status for the lenders from LPC using the Orbis BvD identifiers.

D. Samples and statistics

In this paper, I provide multi-aggregation-level and lender-loan-level analyses. In this subsection, I briefly describe the samples.

Table 1 provides the summary statistics for the two samples at the country level. I consider the nationality of the parent lender of each loan as the source country of the lending flow. Panel A describes the bilateral sample. To construct the bilateral sample, I first select the country pairs with bilateral flows every year between 2000 and 2023 for at least one sector. This leads to a selection of 32 countries on either side of the bilateral relationships. I then expand this set of countries into a balanced bilateral panel with filled zero flows.[19] These countries account for about 20% of all the countries that appeared in the DealScan, but these are the main markets that represent about 97% (94%) of the total transaction values based on the approximated (reported) shares.

Panel B of Table 1 describes the sectoral weight sample. To ensure comparability across these total, domestic, and foreign portfolios and reduce the observations of zeros, I only keep the countries that have both domestic and foreign lending records every year between 2000 and 2023 for at least one sector. This criterion reduces the number of countries further to 20, accounting for 13% of the countries involved in the LPC DealScan database and 95% (92%) of the total loan values based on the approximated (reported) shares.

There are signs of persistent lending exposure. For example, Manufacturing sector took up more than 50% of India's total lending portfolios for four years with an all-year mean weight of 34%. However, there is no sign of systemic dominance of some sectors in the syndicated lending market, as every sector stays in both the domestic and foreign portfolios of at least some country for 20 years or more.

I also construct the lender-loan shares and lender-year sectoral exposures. Loans to borrowers with no sectoral information are excluded when constructing these samples. Table 2 shows the summary statistics for the granular samples. Panel A summarizes the sample at the direct lender-loan level. This sample is employed to test for climate risk management and transfer practices in combination with lender and loan heterogeneity. Hence, I use the reported shares to construct these samples.

To characterize firm-level climate riskiness, I use *EIR* as the main measure of the climate riskiness of a loan. Nationality is determined at the direct lender level in this sample because a lender is more affected by local supervision and local market conditions. Using direct lender nationality can also reasonably absorb the within-group redistribution of brown loans. If a parent-subsidiary brown transfer exists, the loans are more likely to outflow from the country with weaker brown lending resistance.

Panel B of Table 2 summarizes the sample at the parent lender-loan level, using the nationality resumes of the parent operating country. This sample is first used in the parent heterogeneity test for the empirical relationship between relative lending portfolio decarbonization and economic development, with the availability of *EIR* restricting the sample size to $58,000$. I also use this sample to explore the role of lending specialization,

[19]Lists of countries involved in the main samples are provided in Table C2.

measured at the parent lender level, in explaining the cross-border transfer of brown lending. The effective sample size for regressions is restricted by the availability of *RCA*s.

Panel C of Table 2 summarizes the lender-year-level sample, which is used in the supervisory tests presented in Section V.B. This sample is smaller as it only covers the years from 2015 to 2023 and the lenders who have engaged frequently in syndicated lending, i.e., for at least 5 years in this period.[20] The subsample of SSM lenders has similar total exposures compared to the full sample, but they have smaller domestic syndicated loans on average. Among these lenders, 79% are SIs or associated with SIs. This is reasonable as the syndicated loan market is more accessible for larger banks.

I also provide an overview of the sample composition in Figure 1. Part (a) shows how the lender-loan-level sample can be split by lender roles. About one-quarter of the observations concern lead arrangers. Part (b) shows the representation of the main tranche types, with credit lines being the most important type. In part (c), I show the sample distribution across the lender parent types. As expected, the identified lenders with reported shares are mainly banks.

III. Macro analysis: economic development and aggregate loan portfolios

In this section, I provide the country-level analysis. I empirically test whether countries with different economic development levels undergo diverging changes in the sectoral composition of lending portfolios. I also consider the yearly estimates to further investigate how the trends may differ for domestic and foreign lending activities. I then account for other explanatory factors and suggest the channels underlying the empirical observation.

A. Country-level baseline results

I test for the relationship between economic development and carbon sensitivity of lending with bilateral flows, following the gravity model in Equation 4. To exploit the information in the zeros as well, I use the Poisson Pseudo-Maximum Likelihood (PPML) estimator (Silva & Tenreyro, 2006).

Next, I test for a compositional change towards more carbon-productive sectors in the country portfolios as follows:

$$\text{(5)}\quad \text{Sectoral weight}_{iKt} = \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{it-1} + \lambda_{iK} + \lambda_{it} + \lambda_{Kt} + \varepsilon_{iKt}$$

where i indexes the lending country, K the sector and t the year.

This linear regression specification is different from the baseline gravity specification 4 in two ways. First, I take the regression to the linear form without log transforming the dependent variable for more meaningful interpretation while keeping the intended zeros. I estimate the regression using the high-dimensional fixed effects (HDFE) estimator by Correia (2017).[21] The estimated coefficient can then be translated into a direct

[20] About 22% of the lender-year observations were excluded due to this frequency criterion.
[21] I estimate all the remaining linear regressions in this paper using the HDFE estimator.

level change in the sectoral weights of country loan portfolios.[22] Second, I employ different levels of fixed effects. The country×sector fixed effects control for the economic structure of each country. The country×year fixed effects control for all the time-varying changes of a country that would shift the sectoral composition. The sector×year fixed effects control for the time-varying sectoral development.

Table 3 summarizes the country-level baseline results. The first two columns of the table present the bilateral results with the sectoral loan flows for 19 sectors from 2000 to 2023. Column 1 shows the results using all the bilateral flows, including domestic lending. The coefficient estimate is -0.056, significant at the 1% level, meaning that a 1% increase in GDP per capita would lead to an increase of about 0.06 in the carbon sensitivity of lending.[23] However, this relationship is only pertinent in domestic lending, as implied by Column 2. The bilateral lending flows to foreign countries do not show a significant relationship between the carbon sensitivity of lending and log GDP per capita.

The next three columns of Table 3 present the results using the sectoral weights in the total, domestic, and foreign portfolios, respectively. Column 3 reports an estimate of -0.492, significant at the 1% level, suggesting that a 1% increase in GDP per capita would lead to an increase of 0.49 in the carbon sensitivity of sectoral weight in the total portfolio. To illustrate, for two sectors differing in emissions intensity (EI) by one standard deviation, the portfolio weight of the dirtier sector would decrease by an additional 0.71 in response to a one-standard-deviation increase in log GDP per capita ($-0.49 \times 1.53 \times 0.95$) compared to the less dirty sector. This effect is economically meaningful, corresponding to about 10% of the sample mean of the total sectoral weights. This provides direct evidence for a faster sectoral recomposition in the aggregate loan portfolios towards higher carbon productivity in countries with higher economic development.

Consistent with the bilateral results, this overall effect is driven by domestic portfolio reallocation, as shown in Column 4. The domestic portfolio estimate is -0.68 and significant at the 1% level. Similarly, considering two sectors with one standard deviation difference in EIs, the weight difference of the relatively green sector over the brown one in the domestic portfolio increases by 0.99 for a one-standard-deviation increase in log GDP per capita. This domestic effect is also economically large, corresponding to 14% of the sample mean of the domestic sector weights. However, the foreign portfolios of the more developed countries do not manifest a similar sectoral recomposition towards higher carbon productivity, as shown by the insignificant estimate in Column 5.

Following the theoretical framework, a larger domestic response is expected to the extent that higher economic development may have reduced the domestic carbon premium and the loan demand from browner sectors. To inform on the possible causes of this difference between domestic and foreign responses to brown lending resistance, I next estimate how this relationship of interest changes over time.

[22] The results are not sensitive to this change. I tested the relationship with the nonlinear equivalence using the PPML estimator for robustness.

[23] The inconvenience of the nonlinear gravity estimation is that the coefficient here represents a semi-elasticity. It cannot be interpreted as a straightforward level change. This is one important reason why I turn to the linear model for the rest of the paper.

B. Dynamic changes and the domestic-foreign wedge

While the initial analysis examined the average effect over a 24-year period, the impact on foreign portfolios may have only emerged in recent years. To investigate this possibility, I estimate the yearly coefficients of the interaction term in the sectoral weight regressions. A yearly estimate represents how the carbon sensitivity of lending responds to different levels of economic development during the given year. A more negative estimate suggests that the richer countries increasingly outpace the relatively poor countries in terms of loan portfolio decarbonization.

In Figure 2, I present a visualization of how the sectoral decarbonization gap evolves over time. The figure delivers two main messages. First, it shows a gradual enlargement of the sectoral decarbonization gap in the loan portfolios between countries at different levels of GDP per capita. Until 2022, the point estimates are in a downward trend. From 2015 to 2018, the point estimates were significantly negative, most probably in light of the Paris Agreement. The constant fluctuations may be due to the borrowing cycles of the largest borrowers.

Second, there has been a persistent difference between the domestic and foreign portfolios. I refer to this gap as *the domestic-foreign wedge*. The domestic portfolio estimates generally follow the total portfolio trend, while the relationship between the domestic and foreign portfolio estimates is more complicated. The trends for foreign and domestic estimates were similar for some periods, such as 2000-2002 and 2006-2009. During the period around the Paris Agreement, especially 2014-2016, the trends diverged between domestic and foreign estimates. This is consistent with the cross-border redistribution of some sectoral exposures.

For instance, the domestic estimate for 2015 is -1.38, statistically significant at the 1% level, while the foreign estimate is -0.33 with no statistical significance. These estimates mean that, compared to 2000, relatively rich countries had a significantly larger carbon sensitivity of domestic lending than relatively poor countries, but this pattern did not show in their foreign lending portfolios. Combined with a domestic estimate of -0.62 and a foreign estimate of -0.4 in 2014, this provides strong evidence for a reduction in domestic brown lending and some weak evidence for cross-border loan reallocation in anticipation of the Paris Agreement.

In 2016, there was a rebound in the domestic estimate and a decrease in the foreign estimate, which could be explained by the re-adjustment following the reality of the Paris Agreement. The impact of the extensive margin substitution between different sources of financing cannot be ruled out. Some borrowers may have opted for debt financing due to the rapid response of the stock market to the Paris Agreement, which in turn contributed to the domestic rebound seen in 2016.

The results on bilateral lending flows and sectoral weights consistently suggest that economic development does not contribute to the carbon sensitivity of foreign lending at the country level. The difference between domestic and foreign lending here suggests that an arbitrage incentive exists because the intrinsic environmental considerations should lead to a greener allocation in both portfolios.

The missing effect from the foreign portfolios may be caused by international risk transfers, as documented by, for example, Benincasa et al. (2022) and Laeven and Popov (2023). Their findings suggest that banks have increased brown lending abroad while reducing it domestically, which enlarges the carbon wedge between the domestic and foreign portfolios.

On the other hand, the country-level results only provide insights into the market clearing outcomes. Individual lenders may take different approaches to managing climate risk, such as reducing exposure, actively monitoring borrowers' carbon performance, or using a combination of both strategies. Using the lender-loan sample, I consider multiple sources of heterogeneity and examine the lenders' climate risk management and transfer activities in the international syndicated loan market in Section IV.

C. *Brown lending resistance: measurement*

In the baseline results, I use GDP per capita as a proxy for brown lending resistance. In this subsection, I discuss other possible factors that could impact a country's overall brown lending preferences. Based on the portfolio weight specification in Equation 5, I include three different sets of variables in the proxy process for $\log\theta$ to account for the possible omitted variable bias. Each set controls for a distinctive aspect that may affect a country's brown lending resistance. These variables are mildly correlated with GDP per capita, with a magnitude ranging from 0.12 to 0.48.

The first set of variables considers the overall banking operations of each country, including profitability, market power, and capitalization. Bank characteristics are correlated with their environmental preferences (Reghezza et al., 2022). I add to Equation 5 the interaction terms of EI with, respectively, bank deposits to GDP, bank concentration (asset share of the three largest commercial banks), bank non-performing loans to gross loans, bank net interest margin, and bank regulatory capital to risk-weighted assets.

The second factor to consider is a country's financial development. Countries with developed financial sectors respond better to global growth opportunities (Fisman & Love, 2007; Wurgler, 2000). The financial intermediary development can, in turn, affect growth (Beck et al., 2000; Deidda & Fattouh, 2008) and trade (Beck, 2002), which may impact a country's vulnerability to climate change (Bowen et al., 2012). De Haas and Popov (2023) find that more-developed stock markets help to steer investment into more energy-efficient sectors and stimulate green innovation. Even though it is unclear how green stock investments spill over to the loan markets, better development in one or more financial markets is likely correlated with a quicker loan reallocation towards higher carbon productivity.

Similarly, I include the interaction terms to the baseline specification between EI and, respectively, financial system deposits to GDP, mutual fund assets to GDP, total value of stock traded to GDP, corporate bond issuance volume to GDP, and pension fund assets to GDP. Moreover, as I focus on international lending in the syndicated loan market, integration with the foreign market and the syndicated market may have an impact on the estimation. Thus, I additionally include the interaction terms with foreign claims to GDP and syndicated loan issuance volume to GDP.

Apart from patterns related to the financial system, a country's energy demand and preference can impact the development of energy-intensive sectors, which are often the browner sectors. I use heating degree days to control for household energy needs, the renewable energy share in consumption for the sustainability preference, and additionally, the trade of environmental goods for the comparative advantage in the production of environmental goods. They are also included in the baseline specification as interaction terms.

Table 4 provides these results. Columns 1 to 3 consider, respectively, bank operation conditions, financial development, and energy-related factors. Column 4 considers all of these controls simultaneously. Column 5 considers only some of the factors based on their statistical significance from the previous tests, involving bank concentration, syndicated loan issuance volume to GDP, and heating degree days. These alternative estimates vary in magnitude but remain significant. The variations in the estimated magnitude may be partly attributed to the correlation between these additional controls and log GDP per capita. Overall, the results suggest that the empirical observation of differential sectoral decarbonization progresses among countries with different economic developments still holds after accounting for potentially omitted determinants of a country's brown lending resistance.

D. Economic channels

The results so far have shown a significant empirical relationship between economic development and carbon sensitivity of lending in the aggregate portfolios. This is explained by higher brown lending resistance. However, the fact that the changes are predominantly driven by domestic lending also suggests the potential influence of a decreasing domestic carbon premium and a decreasing loan demand from browner sectors in more developed countries. In this subsection, I show that the empirical relationship between GDP per capita and faster sectoral decarbonization is attributed to (at least) three underlying economic channels.

A faster sectoral composition shift by more developed countries may occur through different channels. First, richer countries can be less dependent on carbon-intensive sectors and have more resources for sector-specific adaptation, which leads to a higher propensity for low-carbon transformation of economic structure. Second, countries with higher economic development are likely to have stricter climate supervision or other return-shifting policies or, in general, a better environment to mobilize and facilitate investments into climate solutions. This can affect both the domestic carbon premium, when an institutional component only affects domestic lending, and brown lending resistance when some policy targets all scopes of lending. This is also consistent with better financial knowledge of sustainable investments, i.e., better sustainable finance literacy (Filippini et al., 2024). Lastly, this empirical relationship between economic development and carbon sensitivity of lending can be driven by the pro-environmental values of economic agents, which stimulate sustainable investment activities as observed by Dyck et al. (2019) and Gantchev et al. (2022).

I directly test for these three possible mechanisms driving this empirical relationship using four corresponding measures in the form of interaction terms with EI. I use the indicators from the Notre Dame-Global Adaptation Index (ND-GAIN) to capture the first two driving forces. The *GAIN* index is an aggregate measure of country adaptivity. It is composed of two separate scores, *Readiness* for the ability to leverage investments for climate adaptation and *Vulnerability* for exposure and capacity for adaption. Specifically, a higher *Readiness* score means that the country is more able to mobilize resources for climate adaptation, while a lower *Vulnerability* score means the country has a lower propensity to be damaged by climate hazards. The latter is featured by lower dependency on climate-sensitive sectors, better physical capacity to handle possible climate damage to demography and the economy, and better adaptive capacity of the society and its supporting sectors. All three scores are between 0 and 1. These compound scores comprehensively capture the biophysical, economic, and social factors underlying a country's capacity for economic decarbonization.

Furthermore, I take the *Self–Expression* score from the World Value Survey as a proxy for attitudes toward climate issues, following Gantchev et al. (2022). Countries with more pro-environmental cultures and values may provide more finance to greener sectors. These four scores represent three different but not mutually exclusive mechanisms behind the empirical relationship.

Table 5 shows the results of this second test. As shown in Column 1, the empirical relationship between economic development and carbon sensitivity of lending is mainly driven by differences in country adaptivity, proxied by the GAIN index. Columns 2 and 3 break down this all-around adaptivity measure into two separate aspects of *Readiness* and *Vulnerability*. The results indicate that both high readiness and low vulnerability contribute to faster sectoral changes in the loan portfolios in countries with high economic development. Next, I additionally test if pro-environmental values are another important driver of the observed differential sectoral changes in loan portfolios. The result shown in Column 4 confirms the partial impact of high environmental awareness and pro-social values.

In the last column of Table 5, I include all these factors in one regression and report the estimates in Column 5. The result shows that high readiness and low vulnerability to climate change may be more important factors for high-GDP per capita countries to outpace low-GDP per capita countries in the sustainable lending transition. However, this result is only suggestive due to the high correlations between the Self-expression score and the other three scores, with a size ranging from 0.69 to 0.82.[24]

The scores of *GAIN*, *Readiness*, *Vulnerability*, and *Self–Expression* are highly correlated with log GDP per capita with a magnitude ranging from 0.7 to 0.9.[25] Hence, it is not possible to disentangle these three channels from economic development. For the remainder of the paper, I continue using GDP per capita as the main measure of general brown lending resistance and focus on the sources of international divergence in syndicated loan markets. The within-syndicate variations I use for the following sections facilitate the interpretation through brown lending resistance. The sectoral loan demand

[24] I provide the full correlation matrix in Table C3.

[25] *GAIN* has the highest correlation with log GDP per capita, at around 0.89, while the *Self–Expression* score has the lowest correlation, at around 0.71. More details are shown in Table C3.

differences are not an issue when I examine the intensive margin decisions using firm-level emission intensities, and the return differences are accounted for by the deal fixed effects.

IV. Micro analysis: climate risk-taking on the international loan market

The country-level analysis provides evidence supporting the hypothesis that countries with higher economic development overall show higher carbon sensitivity of lending. However, the result suggests that a persistent domestic-foreign wedge exists, which cannot be explained by the countrywide brown lending resistance.

According to the theoretical framework, a brown lending resistance factor, such as green preferences and climate banking supervision, should deter such lending both domestically and abroad, leading to similar portfolio adjustments. The framework is simplified and ignores the complexity of this international loan market and the heterogeneity in both lenders and borrowers. These factors may have an asymmetric impact on domestic and foreign lending activities.

In this section, I turn to the lender-level analysis, which allows me to rule out effects related to loan returns and demand and account for additional determinants of the market outcomes. I then scrutinize lenders' risk management and international risk transfer activities, exploiting loan and lender heterogeneity.

A. Lender-loan-level baseline results

Exploiting between-lender variations in reported loan shares, I first test the relationship between the brown lending resistance of the lender's home country, as proxied by economic development, and the carbon sensitivity of lending. I adjust the baseline linear specification as follows:

$$\text{(6)} \qquad \text{Loan share}_{lbt} = \alpha + \beta EIR_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt},$$

where l indicates lender, b the loan and t the year. The fixed effects are at the loan×year and lender×year levels. These loan×year fixed effects absorb the impact of borrower characteristics and loan contract characteristics on the lending shares, such as size, maturity, the financial riskiness of the loan, and the corresponding covenant tightness. The lender×year fixed effects absorb the effect of lender characteristics such as overall risk attitude, size, and capital adequacy.

This specification considers loan provision at the intensive margin, comparing the reported shares of the participating lenders to borrowers with different levels of carbon risks, measured by *EIR*. The coefficient of interest is again β. I expect to obtain a negative β, which would indicate that lenders from countries with higher GDP per capita on average show a larger carbon sensitivity after considering the loan, borrower, and lender characteristics.

I report the loan-level baseline result in Table 6, Column 1. These estimates are consistent with the country-level results. The all-loan estimate for β is -0.328, significant at the 0.05 level. It indicates that the relative share reduction from a loan with *EIR* higher by one standard deviation than another loan increases by 19 basis points as the log GDP per capita of the lender country increases by one standard deviation. The foreign-loan estimate is -0.166, which is significant at the 0.1 level. This weaker effect in the foreign portfolio is consistent with the observed domestic-foreign wedge.

The immediate selloff following the origination as documented by Blickle et al. (2020) may threaten the estimation, as the reported shares may not reflect the true retention of loans. It could bias the estimate downward if lenders from more developed countries underwrite more brown loans with the intention of selling them off on the secondary market, i.e. the originate-to-distribute model of lending. This motive behind brown lending may be especially strong when dealing with foreign borrowers, contributing to the domestic-foreign wedge.

According to Blickle et al. (2020), the reported shares in DealScan and the subsequent regulatory filing to the Shared National Credit Registry match better within the lenders whose shares are below 30%. Small share lenders may, in general, have weaker originate-to-distribute intentions because they could have taken a larger share otherwise. To address the selloff concern, I estimate the specification 6 with small share lenders that report a share below 30%.

The estimates concerning small share lenders are negative and significant at the 1% level for both domestic and foreign loans, as reported in Column 2 of Table 6. Lenders participating in Term B loans are often institutional investors with very different preferences. The bank lenders in these loans can also be more likely to sell their shares on the secondary market than lenders in other facilities. In Column 3, I exclude Term B loans, and the associated estimates are unchanged. These results regarding the total portfolios of small share lenders are similar to the lender-loan baseline estimate, while the estimates associated with foreign portfolios are slightly different. Considering only small share lenders, the estimate is larger and more significant than the baseline foreign estimate from Column 1.

These results confirm the empirical relationship between the carbon sensitivity of lending and economic development at the intensive margin. The overall effect size is smaller. This may be due to the negligence of non-participants, which would bias the estimate downward if lenders from more developed countries participate less in the syndication for brown loans. Moreover, the limited data availability of shares and firm-level emissions could also be a reason why this micro-level effect is estimated to be smaller. The lender-loan sample tends to cover more transparent lender-loan pairs, while lenders and borrowers with poor environmental traces may choose not to disclose their information.

To mitigate both sources of biases, I additionally test Equation 5 on the lenders' yearly exposure to sectors. I use the lender-year sectoral weights constructed on both approximated shares and reported shares for comparison. The results of this robustness check are shown in Table C4 in the Appendix. The results are consistent with the intensive margin estimates, with the effect sizes differing across specifications.

For example, the estimate from domestic portfolio weights based on reported shares is -2.083, significant at the 1% level. It means that between two sectors with a one-standard-deviation difference in EIs, the relative reduction in the domestic weight of the browner sector is 2.33 percentage points larger for a lender from a country whose log GDP per capita is higher by one standard deviation. Taking account of both intensive and extensive margin changes, this effect size is economically significant, amounting to 13.5% of the sample mean of these sectoral weights across lenders.

On the other hand, a larger and more significant estimate concerning the foreign portfolios of small share lenders has two possible explanations. First, there can be a stronger originate-to-distribute motive behind brown loan origination among investors from more developed countries (Ouazad & Kahn, 2022).[26] This implies that primary lending institutions intermediate the cross-border financing of climate-risky loans and facilitate the transfer of such risks to less regulated institutions via the secondary market. Second, the results can reflect other important differences between small share lenders and large share lenders apart from the selloff intensity. For instance, larger share lenders are more likely to be lead arrangers, while small share lenders consist of more nonlead participants. The two types of lenders may have different foreign lending preferences.

My data only allows me to further investigate the second possibility. In the next subsection, I examine how the carbon sensitivity of lending changes for lead arrangers and nonlead participants from countries with different levels of brown lending resistance, as well as their foreign lending preferences.

Blickle et al. (2020) also suggest the selloff cases can differ across loan types. In particular, the reported shares are more accurate for bank-targeting loans, including credit lines and Term A loans. In Columns 4 and 5, I repeat the small-share-lender estimation on the subsamples of credit lines and Term A loans, respectively. The estimates for credit lines are similar to the baseline results. However, the estimates concerning Term A loans are peculiar, indicating no international divergence among lenders of these loans and even a weak reversed trend when these loans are foreign.

These results for Term A loans can be related to special characteristics of the borrowers with whom lenders choose to use Term A loans. These borrowers tend to have low credit risk profiles and strong cash flows to make scheduled repayments during the amortization over 5-7 years. The lack of effect implies that lenders may be more inclined to prioritize liquidity over climate-related risk management when dealing with prime borrowers. Note that these estimates may be imprecise because of the small number of observations.

Overall, these results reveal that loan heterogeneity impacts the empirical relationship of interest. Lenders may deliberately choose different loan types to finance borrowers with different emission intensities as a means of climate risk management.

B. Heterogeneity in brown lending preference

In this subsection, I examine how lender and loan heterogeneity contributes to this international transfer of brown loans.

Lead arrangers and other underwriting agents differ from pure participants in two main aspects. First, agents are tasked with due diligence and are better informed about the

[26] LaCour-Little et al. (2024) has recently cast some doubts on the results from Ouazad and Kahn (2022). My result aligns to some degree with Ouazad and Kahn (2022) in that securitization remains a possible reason for observing different results with small share lenders.

borrower's riskiness than the non-agent participants. Second, the non-agent participants mainly accrue interest on the loan, while lead arrangers and other agents also receive commission fees for the arrangement and other administrative services.

Agents and non-agent lenders may have different preferences for brown loans. The informational advantages may lead to better climate risk management by agents. Moreover, agents may prefer to make fee incomes, which are not directly impacted by climate risks, and only retain the necessary shares.

In the first test, I distinguish between agents that are involved in the underwriting process (*Agent*) and the other lenders (hereafter participants). I saturate the specification 6, interacting *Agent* with *EIR*, log GDP per capita, and $EIR \times$ log GDP per capita. The coefficient for $Agent \times EIR$ informs me whether agents and non-agent participants retain shares differently in brown loans. The coefficient for the triple interaction suggests whether the two types of lenders contribute to the international transfer of brown loans differently.

The estimation result is reported in Column 1 of Table 7. The coefficient for $Agent \times EIR$ is not significantly different from zero, suggesting no general difference between agents and participants regarding brown lending. The coefficient for $EIR \times$ log GDP per capita is negative and significant, while the coefficient for $Agent \times EIR \times$ log GDP per capita is again insignificant. It indicates that agents from countries with higher brown lending resistance behave similarly to the participants.

The *Agent* lenders consist of a broader group of agents that are more likely engaged in the underwriting activities. There can still be heterogeneity within this group, i.e., between *Lead Arranger* and other agents. Lead arrangers often retain a larger share, which reflects more than their own demand for this brown asset.

There are two main theories on lead arrangers' larger retention. First, this retention signals the quality of loans and commitment to future monitoring (Sufi, 2007). Second, lead arrangers solve a demand discovery problem and must retain the residual loans (Bruche et al., 2020). This risk is referred to as the pipeline risk.

Lead arrangers may hold more brown loans following both theories. First, as climate risks become more severe, interest-based returns from brown loans are under higher uncertainty. A loan is usually repaid over several years, and any climate-related shock can affect the ability of a brown borrower to repay. As non-lead lenders become more concerned with climate risks, lead arrangers are more incentivized to hold larger shares to signal loan quality and their commitment to future monitoring. Second, if more lenders avoid brown loans to mitigate their climate risk exposure, the lead arrangers may be stuck with residual loans and retain more. This additional pipeline risk may be weaker for lead arrangers from more developed countries, as the chances of them transferring the loans to institutional investors via the secondary market are higher.

I perform a similar test to compare the lead arrangers to the other agents and report the result in Column 2 of Table 7. The coefficient of $Lead\ Arranger \times EIR$ is 9.736, significant at the 0.05 level. This means that compared to non-lead agents, lead arrangers retain a significantly higher share of browner loans. This result is consistent with the hypothesis that lead arrangers may face a stronger pipeline risk when arranging a browner loan or need a stronger signal for the quality of the loan.

The coefficient of *Lead Arranger* $\times$ *EIR* $\times$ log GDP per capita is significantly negative. Combined with the insignificant estimate on *EIR* $\times$ log GDP per capita, it means that lead arrangers from countries with more brown lending resistance have a higher carbon sensitivity of lending, while non-lead agents do not show such differentials. Based on the evidence that lead arrangers retain a larger share in browner loans, the negative estimate for the triple interaction term can also support the hypothesis that lead arrangers from richer countries face weaker pipeline risks for brown borrowers due to institutional demand.

Some lenders manage the climate risks on their portfolio by carefully selecting which loan package to participate in and negotiating the loan terms. Ivanov et al. (2023) document that some lenders switch from term loans to credit lines to fund vulnerable borrowers following the Cap-and-Trade policy. Credit lines are characterized by a revolving nature with a shorter duration of exposure, on-demand access to funds, and often stricter financial covenants. On the other hand, a term loan is usually repaid on a fixed schedule over several years. Any climate-related shock can hit the ability of brown borrowers to repay and cause losses. Under higher climate risk management pressure, nonlead lenders may increasingly use credit lines to manage their climate risk exposure. This can lead to differential demands for the two types of loans by nonlead lenders, impacting the retention of the lead arrangers in these loans.

I distinguish between credit lines and term loans and test the previous specification again. This additional test sheds light on how this means of climate risk management affects the lead arrangers' retention of brown loans. The results are shown in Columns 3 and 4 of Table 7.

There is large heterogeneity in retention between credit lines and term loans. The estimate for *Lead Arranger* $\times$ *EIR* is 12.473 in Column 3, significant at the 1% level, while it is insignificant in Column 4. It suggests that the additional shares retained by the lead arrangers mainly occur within term loans. This is consistent with the risk management using credit lines documented by Ivanov et al. (2023) and Brown et al. (2021).

Furthermore, the evidence shows that the driving players behind the international transfer of brown loans are different for credit lines and term loans. The estimate for *EIR* $\times$ log GDP per capita is significant and negative in Column 3. This means that, among credit lines, lenders from countries with higher brown lending resistance generally show stronger carbon sensitivity of lending. Lead arrangers and other lenders respond similarly to the changing environment, as indicated by an insignificant estimate for *Lead Arranger* $\times$ *EIR* $\times$ log GDP per capita in Column 3. However, only lead arrangers in term loans show this tendency to decrease retention as the brown lending resistance of their home countries intensifies, as shown by a significant negative estimate for *Lead Arranger* $\times$ *EIR* $\times$ log GDP per capita combined with an insignificant estimate for *EIR* $\times$ log GDP per capita in Column 4.

In Column 5 of Table 7, I directly test for lead arrangers' differential retention in term loans versus all other loans. Lead arrangers often contribute a large amount to the loans and have the same need for climate risk management for their portfolio, especially when the brown lending resistance strengthens. This internal management of climate risks may be partially done by reducing exposure to these brown borrowers in the form of term loans. The negative estimate of *Term Loan* $\times$ *EIR* $\times$ log GDP per capita confirms this hypothesis, which is significant at the 1% level.

These results again reflect intensive margin changes only. The magnitude of the international transfer of brown loans may be larger if I take into consideration the extensive margin changes.[27] Overall, there is evidence that lenders have become more aware of the potential financial consequences of climate risks and actively manage their risk exposure by increasing the use of credit lines.

C. Cross-border risk transfer

A natural follow-up question is how the observed heterogeneity across lender roles and loan types may affect lending outcomes differently for domestic and foreign loans. I directly test for the difference between foreign and domestic lending by interacting *Foreign* with *EIR*, log GDP per capita, and *EIR* $\times$ log GDP per capita. I first examine whether lead arrangers show different domestic and foreign responses to the rising brown lending resistance from their home countries. I then perform this test on credit lines and term loans separately, where I again distinguish between lead arrangers and other lenders. The key variables here are *Foreign* $\times$ *EIR* and *Foreign* $\times$ *EIR* $\times$ log GDP per capita. The two coefficients measure, respectively, how an average lender behaves differently in a foreign loan and how the foreign lending preference changes as brown lending resistance grows in the home country.

The results are shown in Table 8. The estimates from Column 1 indicate no significant difference in lead arranger's retention between domestic and foreign loans. Furthermore, a higher brown lending resistance in the home country is significantly associated with a higher carbon sensitivity of lending among lead arrangers, similarly for domestic and foreign loans.

Through Columns 2 to 4, I focus on the credit lines and consider all lenders, lead arrangers, and other lenders, respectively. The estimates for *Foreign* $\times$ *EIR* are negative and significant for all lenders in Column 2 and nonlead lenders in Column 4. For the same groups, the estimates for *Foreign* $\times$ *EIR* $\times$ log GDP per capita are positive and significant.

Among credit lines, lead arranger retention of brown loans does not differ significantly for domestic and foreign cases, while other lenders tend to retain less of a foreign brown loan than of a domestic brown loan. This is consistent with the notion that non-lead lenders suffer more from information asymmetry, which is more severe with a foreign borrower. Furthermore, non-lead lenders from a high-resistance country tend to adjust their foreign retention significantly less than their domestic adjustment.

From Columns 5 to 7, I turn to the term loans. The estimates of interest are insignificant throughout these columns, except for a significantly negative estimate for *EIR* $\times$ log

[27] Some papers study banks' extensive margin changes for climate risk management. For example, Meisenzahl (2023) shows that banks adjust their loan balances across areas with different degrees of climate risks at an extensive margin.

GDP per capita in Column 6 concerning lead arrangers. Among the term loans, lenders of different roles show similar preferences for domestic and foreign brown lending. In the face of stronger brown lending resistance, lead arrangers retain a significantly smaller share in browner loans, while other lenders do not change their lending patterns significantly.

In the previous analysis, I find consistent evidence for differential lender responses to domestic and foreign brown borrowers, i.e. a domestic-foreign wedge in the carbon sensitivity of lending. Lenders are more inclined to reduce brown lending domestically than abroad when brown lending resistance increases in their home countries.

Two factors may have contributed to this domestic-foreign wedge in the carbon sensitivity of lending. First, as the brown firms from high-resistance countries bear a rising carbon cost, the brown returns from lending to low-resistance countries may become disproportionately higher for lenders from high-resistance countries. This return-seeking incentive may drive cross-border brown loan relocation.

My finding that non-lead lenders of credit lines show a weaker response to higher brown lending resistance in terms of foreign lending is consistent with this first incentive. As this effect only exists within credit lines, the use of which is a tool to create flexibility for climate risk management, it provides indirect evidence that many lenders prefer to actively manage their climate exposure rather than forgoing lending opportunities.

The second cause behind the domestic-foreign wedge is that a country's brown lending resistance does not equally impact all domestic lenders in reality. The selloff problem discussed previously is an example of how brown loans may have been transferred to less regulated lenders. This room for regulatory arbitrage can lead to both a domestic transfer across different types of lenders and an international transfer exploiting higher risk premiums in less regulated countries.

To provide evidence for this second factor, I further explore the heterogeneity of parent lenders. I first test the baseline specification in Equation 5 on the total shares by a parent lender in a loan. Then, I repeat this estimation on banks and nonbanks, respectively.

I expect the observed relative reduction in brown loan retention to be mainly attributed to banks because they are more regulated. Although climate banking supervision has not been formalized in many countries, the expectations about when and what measures may be introduced may have already entered banks' decision-making process and triggered portfolio decarbonization.

Lastly, I further divide financial institutions into weak and non-weak lenders based on their Tier 1 capital ratio. I expect overall better-capitalized lenders to show a larger reduction of brown loan retention in response to higher brown lending resistance, as they have more capital capacity for incorporating climate consideration (Reghezza et al., 2022).

However, well-capitalized lenders may, in fact, be more able to reallocate brown lending across borders for profits. Well-capitalized lenders are usually under less supervisory pressure. Moreover, they are less vulnerable. These lenders can afford costly monitoring throughout the loan duration and have capital room to take this risk. Although some papers, such as Laeven and Popov (2023), have argued that weakly capitalized lenders may engage in more cross-border reallocation of brown loans due to their risk-taking preference, the empirical result does not support their theory. On the contrary, Meisenzahl (2023) finds evidence that weak banks retreat more from areas with high climate risks, which is in line with the higher vulnerability of weak banks to climate risks. This is also supported by the capital scarcity argument from Irani et al. (2021).

I conduct these tests at the parent level to avoid the impact of organizational complexity. The supervisory scope is often determined at the highest level within a financial group (within a country). If a direct lender is a subsidiary of a large bank, it is also under more supervisory pressure than a subsidiary of an unsupervised institution. Hence, it would be imprecise to make this distinction at the direct lender level. This parent-level test can also serve as a robustness check for the concern that parent lenders use their foreign subsidiaries to expand brown credits (Demirgüç-Kunt et al., 2024).

The estimation result is reported in Table 9. As shown in Column 1, the re-estimated baseline results at the parent lender level are consistent with the previous analysis. The parent lenders from high-resistance countries show a higher carbon sensitivity of lending. This also holds for foreign loans, albeit to a smaller extent.

Columns 2 and 3 compare banks with non-banks. Bank lenders from high-resistance countries reveal a higher carbon sensitivity of lending. When focusing on foreign loans only, the estimate is similar in size but more significant. This implies that banks respond to higher domestic brown lending resistance with greater reallocation away from foreign brown borrowers, similar to a flight home effect (Giannetti & Laeven, 2012). The result is expected to the extent that it is less costly for banks to monitor domestic borrowers and even engage in their climate risk mitigation. Moreover, domestic and foreign banks use different lending technologies (Beck et al., 2018). This reallocation in favor of domestic brown borrowers may be a result of relationship lending by domestic banks, which lowers their cost of lending and increases their willingness to provide loans (Petersen & Rajan, 1995).

For non-bank lenders, the higher brown lending resistance of the home country is not associated with a higher carbon sensitivity of lending, as expected. The result is similar with or without domestic loans. This difference between bank and nonbank lenders is expected as they have different lending preferences and strategies.

Columns 4 and 5 focus on the lenders subject to capital requirements, which include banks and some other financial institutions. I define weak lenders as those within the bottom 25% of the Tier 1 ratio distribution. The estimates for weak lenders are significantly negative with or without domestic loans. This means that weak lenders from high-resistance countries show greater carbon sensitivity of lending in both domestic and foreign portfolios than those from low-resistance countries.

The all-loan estimate for the better-capitalized lenders is significantly negative, as shown in Column 5. This effect is larger than that of weak banks. At the same time, I do not observe this pattern within foreign loans.

My findings suggest that weak lenders become more active in reducing their exposure to brown borrowers as the brown lending resistance increases in their home countries.

They do so both domestically and abroad.[28] However, a higher brown lending resistance impacts the non-weak lenders mostly on their domestic adjustments. Non-weak lenders from countries with different levels of brown lending resistance do not seem to behave differently in their brown share retention abroad. This divergence between all-loan and foreign-loan results implies that these less vulnerable lenders from high-resistance countries have taken different climate risk management approaches for their domestic and foreign portfolios.

I interpret this result as a combined outcome from both return-seeking and regulatory arbitrage incentives. A country with higher brown lending resistance is more likely to have more stringent environmental policies, which reduce the return of domestic brown loans. The relatively better-capitalized lenders exploit the higher brown returns by replacing the domestic brown loans on their portfolios with foreign ones, i.e., "relocation" of brown loans.[29] This provides an important aspect of climate policy spillovers.

It is unclear what consequences these reallocation activities may have on lenders' performances. It is possible that this brown loan redistribution is efficient. These lenders might have screened out higher-quality foreign borrowers and used contract design to overcome information asymmetry (Beck et al., 2018). However, these changes can also increase system risks if lenders from more developed countries become more inclined to follow an originate-to-distribute model, underwriting brown foreign loans to facilitate these loans' distribution on their home secondary markets.

Due to data constraints, I cannot examine secondary market activities. However, it is possible to inspect some efficiency-related differences among lenders and the associated impact on their foreign brown lending. I show how one aspect of such differences, i.e. lender specialization, drives this type of credit reallocation in Section V.

V. Drivers of reallocation of brown loans

My findings suggest two types of reallocation of brown loans are occurring via the international markets. First, there is a transfer of brown loans from more-regulated lenders to less-regulated market players, in line with Ivanov et al. (2023). Second, uneven changes in carbon sensitivity between domestic and foreign portfolios of high-resistance countries suggest the existence of a cross-border transfer by lenders in these countries. The slower foreign portfolio decarbonization is mainly attributed to credit line lenders, non-banks, and relatively better-capitalized lenders.

Which factors have facilitated such risk transfers? In this section, I discuss two pertinent factors that stimulate the reallocation of brown loans: lender specialization and soft supervisory measures that create a disparity.

[28]Previous literature such as Reghezza et al. (2022) provides some evidence that weak banks are lagging behind well-capitalized banks in portfolio decarbonization. My result does not contradict this line of literature as it concerns a different question. My estimate describes how (weak) lenders from different countries show differential tendencies in share retention of brown loans. It does not compare weak and non-weak lenders from the same country.

[29]The difference in the all-loan estimates between weak and non-weak lenders supports this interpretation. Banks with higher capital levels have previously been shown to contribute more to the same loan (Chu et al., 2019). If the environmental concerns affect weak and non-weak lenders in the same way, I should have observed a less negative estimate for the better-capitalized lenders.

A. Brown specialization

One key incentive behind cross-border reallocation is to exploit higher returns on foreign brown loans, especially when domestic returns drop in high-resistance countries. I expect this incentive of cross-border reallocation to be particularly pertinent for lenders that specialize in brown lending.

Lenders specialize by concentrating their lending in industries where they have superior knowledge and connections. This specialization facilitates their information acquisition, including ex-ante screening and ex-post monitoring, and can improve contracting efficiency and lower the likelihood of loans becoming non-accruing (Blickle et al., 2023; Giometti et al., 2024).

Several papers have implied a relationship between banks' lending specialization and their foreign market presence, such as Chu et al. (2021) and Paravisini et al. (2023). For lenders who specialize in lending to brown sectors, the increasing relevance of climate risks may increase the impact of their comparative advantage (Chu et al., 2021). By continuing brown lending, they can benefit from both higher returns in foreign countries caused by a gap in environmental regulatory stringency and potentially reduced competition due to the green preferences of some other lenders.

I examine the impact of lender specialization on the carbon sensitivity of lending using Relative Comparative Advantage (*RCA*) measures that capture a parent lender's prior experiences in each sector, i.e., the weight of a given sector in a lender's portfolio relative to the weight of this sector in the total lending.[30] A lender with a higher RCA for the given sector is considered to be more advantageous in lending to this sector.

As the lender specialization is measured at the sector level, I focus on how the sectoral patterns of a borrower interact with this lender preference by employing the sectoral emission intensities. I estimate the following specialization:

$$\begin{aligned}
\text{Total share}_{lbt} = {} & \alpha + \beta\ EI_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \gamma_1\ RCA_{lt-1} \\
& + \gamma_2\ RCA_{lt-1} \times EI_{bt-1} + \gamma_3\ RCA_{lt-1} \times \log(\text{GDP per capita})_{lt-1} \\
& + \gamma_4\ RCA_{lt-1} \times EI_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt},
\end{aligned} \tag{7}$$

where *EI* is the sectoral-level emission intensity. The dependent variable is the total loan shares by a parent lender. I consider the parent-level shares to mitigate the concern associated with indirect lending through subsidiaries.

The use of *EI* also increases the sample size more than sixfold because borrowers without firm-level emission intensity data are also kept in the sample. The informational wedge between specialized lenders and non-specialized ones would be more acute when dealing with opaque borrowers (Paravisini et al., 2023). Blickle et al. (2023) find that specialized banks are more willing to lend to more opaque firms in their industry of specialization. This choice also allows me to capture the lending relationships between specialized lenders and more opaque firms.

As in the baseline specification, β measures how a lender's carbon sensitivity of lend-

[30]The details of variable construction are provided in Section II.A.

ing changes with the level of home-country brown lending resistance. Additionally, this Specification 7 compares the total retention at the parent lender level across lenders with different sectoral specializations. The coefficient γ_1 captures the direct impact of sectoral specialization on the total shares retained. I expect γ_1 to be positive for both domestic and foreign lending. The coefficient γ_2 informs whether and to what extent the climate consideration may slow down the brown credit expansion induced by specialization. I expect γ_2 to be negative because sectoral specialization may not be able to fully offset the adverse impact of climate risks. For instance, lenders specializing in brown lending can still bear a loss caused by natural disasters.

Moreover, γ_3 suggests how this effect may vary in size for lenders from different countries. This coefficient is of less interest because it is essentially a lender characteristic. It would have been absorbed by the lender-year fixed effects if *RCA*s were not smoothed out over a period of three years. I include this interaction term for completeness.

The coefficient γ_4 is of the most interest. It directly tests if and how the relationship between a lender's carbon sensitivity of lending and the degree of home-country brown lending resistance depends on the sectoral specialization of this lender. Specialization can be an important determinant of how feasible it is for lenders to shift their portfolios toward greener sectors in light of a tightening environment. I expect γ_4 to be positive, meaning that more specialized banks are less inclined to reallocate credits away from their specialized sectors in response to increasing brown lending costs.

Table 10 summarizes the results. Columns 1 and 2 first provide the baseline results without adding *RCA* and the associated interaction terms, respectively, for all loans and foreign loans. The baseline estimates feature a significantly negative relationship between lenders' overall carbon sensitivity of lending and the brown lending resistance of their home countries and a weaker relationship among foreign loans, consistent with the previous analysis.

In the remaining columns of Table 10, I estimate the specification 7 on all loans and foreign loans using two different sets of *RCA* measures, which I constructed using both the reported and approximated shares. As discussed in Section II.A, the reported shares are sparsely available. As a result, RCAs based on reported shares may underestimate brown specialization if banks intentionally underreport their participation in brown loans. To mitigate this concern, I constructed alternative RCAs based on approximated shares. These approximated shares provide a reasonable amendment for the possible bias related to the conditional availability of loan shares, as the approximation error is uncorrelated with the climate-related characteristics of the loan.

Columns 3 and 4 report the estimation results using the *RCA*s based on reported shares, and Columns 5 and 6 use the *RCA*s based on the approximated shares. These results are consistent and provide support for my hypotheses. The coefficient for *RCA* is positive throughout these columns, suggesting that lenders retain a larger share of a loan if they specialize in the sector of the borrower. The coefficient for $RCA \times EI$ is estimated to be negative in all columns but only significant in foreign loans. To interpret, lenders with browner specialization tend to downsize their foreign expansion compared to lenders specializing in a less carbon-intensive sector, ceteris paribus. This does not seem to be the case in their domestic lending, as implied by smaller estimates in Columns 3 and 6 that are, respectively, only weakly significant and insignificant. This result is consistent with my hypothesis that possible losses from climate risks may offset the lending advantages for lenders specializing in brown sectors.

The coefficient for $RCA \times EI \times$ log GDP per capita is estimated to be positive in all columns. In particular, in Columns 4 and 6, the estimates are significant at the 1% level, suggesting that brown-specializing lenders from high-resistance countries cut brown credits abroad by less compared to similar lenders from low-resistance countries. Notice that, after isolating the impact of bank specialization on how lenders' carbon sensitivity of lending responds to brown lending resistance in their home country, the estimates for $EI \times$ log GDP per capita become larger, and they become significantly negative at the 1% level. This means that the domestic-foreign wedge in the high-resistance countries' carbon sensitivity of lending is directly attributed to the transfer of brown lending to foreign countries by specializing lenders in these sectors. These results are consistent with my hypothesis that brown specialization is a key determinant of how lenders respond to climate-related measures in their home country.

The only difference in estimation when using the alternative *RCA*s is regarding $RCA \times$ log GDP per capita among foreign loans. This estimate is significantly negative in Column 6 but not in Column 4. A significantly negative estimate for $RCA \times$ log GDP per capita indicates that the additional lending interest associated with specialization is weaker for lenders from countries with better economic development. This difference is probably because this alternative *RCA* captures more diversified portfolios for lenders from more developed countries with the loan share approximation.

Overall, the results provide evidence that lender specialization is an important factor behind the observed cross-border reallocation of brown loans. This transfer of brown loans by specialized lenders is more pertinent when their home country has a higher brown lending resistance.

B. ECB's climate guide and supervisory expectations

So far, I have used economic development as a proxy for a country's brown lending resistance. This proxy focuses more on the international disparity among countries but might overlook dynamic regulatory changes within a country or a region.

According to the theoretical framework of this paper, a climate supervision measure that targets all lenders on all their lending activities is supposed to lead to less brown lending in both domestic and foreign portfolios. In reality, financial supervision is costly and thus cannot cover all lenders equally. One such example is the Single Supervisory Mechanism (SSM), whereby the European Central Bank (ECB) carries out financial supervision over the Eurozone financial institutions in the principle of proportionality. It was officially launched in 2014, covering 19 member states in the Eurozone. In late 2020, Croatia and Bulgaria joined on a voluntary basis.[31]

[31] The current participant countries are Belgium, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Austria, Portugal, Slovenia, Slovakia, Finland, Estonia, Bulgaria, and Croatia.

The SSM features a combination of direct and indirect supervision by the ECB. A list of credit institutions and financial holding companies are classified as Significant Institutions (SI) and are directly supervised by the ECB. The ECB typically reviews and evaluates the risk profiles, conducts stress tests, makes supervisory dialogues (including on-site file auditing), and imposes enforcement measures and even sanctions. The significance criteria include size, economic importance, cross-border activities, and direct public financial assistance. Apart from SIs, other supervised entities are classified as Less Significant Institutions (LSI) and are supervised by national supervisors under the oversight of the ECB.[32]

In November 2020, the ECB published the Guide on climate-related and environmental risks (hereafter "the Guide") and officially incorporated climate supervision into its supervisory scope. The Guide communicates to SIs and LSIs how the ECB expects them to understand climate-related and environmental risks and integrate these risk considerations into their organizations and operations, with more reporting and assessment being required.

As set out by the Guide, climate risk becomes a part of direct supervision practices for SIs, leading to a disparity in climate supervision. The ECB started directly monitoring the climate management progress of SIs as soon as the Guide was published. LSIs are left to their national competency authorities, who are in different stages of adopting the proposed approach nationally. In Appendix B, I provide a detailed description of the ECB's climate supervision evolution.

The fact that the SSM structure imposes different supervision intensities for lenders in the SSM region provides a quasi-experiment setup to study how the changes in the supervisory environment can affect credit allocation decisions. The criteria for determining SIs do not consider the climate risk exposures of the supervised entities, which makes this change in supervisory pressure from the publication of the Guide exogenous to these institutions' climate risk-taking.[33]

How would formal supervisory expectations change brown lending by SSM lenders? Compared to, for example, a supervisory policy in Brazil that mandated large banks to incorporate climate risks into capital adequacy assessment in 2017, the ECB Guide sent a softer signal, which did not impose rules of mandatory compliance nor consequences for violation at the time of publication. Arguably, there should be only weak or even no effect on the intended group, which is SIs.

Concerning the rule-based climate supervision measure taken by Brazil in 2017, Miguel et al. (2024) find the targeted banks reallocate credits away from exposed sectors. However, they also find an unexpected expansion of credits by smaller banks that cancel out the potential real effects of the policy. The Guide shares the unequal nature of supervision and thus could also unintentionally relieve the supervisory pressure faced by non-SI lenders. Specifically, I hypothesize that the weak supervision and supervisory disparity

[32]The information about the SSM and ECB's supervision practices is from the official website of the ECB. For more details, see https://www.bankingsupervision.europa.eu.

[33]The same idea was argued and used in Aiello (2024), where the author investigated the credit allocation to Italian firms using European supervisory data.

implied by the Guide would lead to little reduction of brown lending by SIs. On the contrary, it could increase brown lending by less regulated lenders.

I test my hypothesis in two steps. First, I test for the local effect of the Guide publication by comparing the sectoral weights of SIs to those of other lenders located in the SSM area, starting from 2015.[34] I estimate the following triple difference-in-difference (DDD) specification at the direct lender level:

$$\begin{aligned} \text{Sectoral Exposure}_{lKt} = & \alpha + \gamma_1 EI_{Kt-1} \times SI_{lt} + \gamma_2 EI_{Kt-1} \times SI_{lt} \times Post\ Guide_t \\ & + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}, \end{aligned} \tag{8}$$

where l indicates the lender, K the sector and t the year. *SI* indicates if the lender is *treated*, i.e., directly supervised at the direct or parent level, and *Post Guide* indicates the years from 2020 to 2023. I consider the yearly reported sectoral loans to all borrowers, domestic borrowers, and foreign borrowers, respectively, as dependent variables.[35]

I do not include the baseline interaction term of $EI \times \log \text{GDP}$ per capita here because I focus on SSM-area lenders in this test, and I expect the overall brown lending resistance to be similar within the Eurozone. The coefficient γ_1 shows whether general supervisory intensity was correlated with sectoral exposure before the shock, and γ_2 reveals whether the Guide has shifted the treated lenders' sectoral allocation across sectors as intended. A negative γ_2 would suggest that the Guide has led treated institutions to deepen their transition more than the control group.

The potential issue with this first estimation is that the control group is unlikely to be "untreated" in effect. If the Guide unintentionally relieves the climate-related supervisory burden faced by non-SI lenders in the SSM area, they might even increase brown lending during the post-shock period, which would result in overestimating the treatment effect.

To mitigate the bias and shed light on the potential unintended effects, I consider lenders who potentially receive a reversed signal as another treated group, consisting of non-SI lenders with direct lending subsidiaries or parents located in the SSM area. I refer to this group as *Other SSM-related lenders*. This group of lenders are most likely to be "beneficiaries" of the Guide. If they expected stricter measures before, the soft supervision and unequal implementation revealed by Guide would have led them to adjust their portfolio adversely. I should see a rebound in their brown exposure following the Guide in this case. Moreover, if a targeted lender decides to discontinue some brown loans after the Guide, another lender who is from the same area but subject to less climate supervision will have a higher chance of being the replacement.

[34] The lists of supervised entities are available from 2015 on, and this period also covers the years after the Paris Agreement, avoiding possible preference changes around the event.

[35] I focus on loan amount following the literature such as Aiello (2024), Meisenzahl (2023), and Miguel et al. (2024). As I fill the zeros when a lender does not lend to a certain sector in a year, I do not take the log of the outcome variable as Miguel et al. (2024) and Aiello (2024) do. Meisenzahl (2023) also directly uses the level of the outstanding loan balance.

I then test a specification that compares three groups for the same period (2015-2023):

$$
\begin{aligned}
\text{Sectoral Exposure}_{lKt} = {} & \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} \\
& + \gamma_1 EI_{Kt-1} \times SI_{lt} + \gamma_2 EI_{Kt-1} \times SI_{it} \times Post\ Guide_t \\
& + \gamma_3 EI_{Kt-1} \times Other\ SSM - related\ Lender_{lt} \\
& + \gamma_4 EI_{Kt-1} \times Other\ SSM - related\ Lender_{lt} \times Post\ Guide_t \\
& + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}.
\end{aligned} \tag{9}
$$

Note that I included the baseline interaction term back in this specification because more countries are involved here. I expect the general brown lending resistance from the lenders' home countries to still play an important role.

The control group changes when moving from Specification 8 to Specification 9. The control group is now the lenders that do not operate in the SSM area nor have an SSM parent, i.e., a "unrelated" group. The coefficient γ_1 compares the pre-shock sectoral weights of treated lenders to the unrelated group, and γ_2 captures the shock-induced change in the difference between the two groups. Next, the coefficient γ_3 compares the pre-shock sectoral weights of the other related lenders to the same unrelated group, and γ_4 considers how the comparison outcome changes after the publication of the Guide between them.

The coefficients of interest are γ_2 and γ_4.[36] If this soft supervisory measure backfires, I expect γ_4 to be positive. And if this occurs, γ_2 should be different from the estimates from Specification 8.

I report the estimation results in Table 11, with Columns 1 to 3 for the first test using Specification 8 and Columns 4 to 6 for the second test using Specification 9. The first set of results compares the carbon sensitivity of lending between SI and non-SI lenders in the SSM region in their total, domestic, and foreign portfolios. The coefficients for $EI \times SI$ are negative throughout the three columns but statistically insignificant. It implies that the ECB general supervision without specific climate requirements has impacted SIs and non-SI lenders similarly.

Importantly, the coefficients for $Post\ Guide\ \times EI \times SI$ are estimated to be negative for all three portfolios, significant at the 5% level for total and domestic portfolios. This result suggests that the supervisory expectations set out by the Guide have shifted the SI lenders' brown exposures in a meaningful way as compared to non-SI lenders. This finding aligns with Aiello (2024) and Miguel et al. (2024), where SIs have reallocated credits away from polluting (Italian) firms. However, the SI and non-SI lenders continued to lend to foreign brown sectors in a similar way even after the Guide. This divergence in domestic and foreign lending changes is consistent with a cross-border risk transfer.

In Columns 4 to 6, I compared two different treated groups, namely SIs and other SSM-related lenders, to a third group consisting of the unrelated lenders. The baseline result related to $EI \times \log \text{GDP}$ per capita remains the same as in the previous analyses.

[36] There is no obvious reason why the SSM-related lenders would behave differently compared to the control group, especially in a way that is independent of their home country's brown lending resistance. I leave the relationships implied by γ_1 and γ_3 as a secondary empirical question.

However, the results regarding the post-shock changes are completely different from this broader perspective.

I highlight two key deviations when taking unrelated lenders as the control group instead of non-SI SSM lenders. First, the new result suggests that the Guide publication has had an adverse effect on SIs' carbon sensitivity of lending, indicated by the positive estimates throughout Columns 4 to 6. They are statistically significant at the 1% level. Second, I find that the other SSM-related lenders significantly increase their lending to browner sectors following the Guide, in line with the small bank expansion documented in Miguel et al. (2024). This rebound is large in size and exists in both domestic and foreign portfolios.

To confirm that this change in the sectoral exposure is most likely caused by the publication of the Guide, I additionally estimate the yearly differences in carbon sensitivity of total lending between the SIs, non-SI SSM lenders, and the new control group. In Figure 3, I show how the yearly estimates regarding SIs' carbon sensitivity evolve relative to the unrelated group. The two groups of lenders only started to show significant differences in their carbon sensitivity when lending during 2020.[37]

The observation of decreased deviations during 2022 and 2023 is consistent with the ECB's tightening attitude toward the non-alignment of banks' practices with green expectations during that time, as revealed by the use of language during the public talks. In 2022, the ECB launched a climate risk stress test and published the results. In 2023, public communications started to emphasize credible consequences of non-compliance, including penalty payment and actions on banks' Pillar 2 capital requirements.[38]

Although the alternative control group can be different from the SSM-related lenders in other aspects, such as syndication preferences, the much larger estimates on the non-SI SSM lenders as compared to SIs provide support for the unintended adverse effect hypothesis. This finding should raise regulatory concerns. If ignoring the possible reverse interpretation of the Guide by less regulated lenders, the comparison between SI and non-SI lenders within the Eurozone cannot reveal the true changes in the brown lending exposures and may be misleading. Moreover, lenders can reallocate credits across borders through connected international financial markets. As a result, a soft and partial climate supervisory measure in one country (region) can lead to not only uneven changes in brown exposure across lenders under disparate supervision but also more brown financing towards foreign countries.

VI. Conclusion

Are financial institutions effectively supporting efforts to combat climate change, or are they primarily redistributing climate-related financial risks across markets? While risk redistribution may offer short-term benefits to financial institutions, it undermines the global transition to carbon neutrality.

[37] A similar trend regarding non-SI SSM lenders is shown by Figure C1. Their rebound in brown lending started to show in 2021 and peaked in 2022.

[38] I provide a summary of these keywords in Figure B1.

This paper examines how these two competing incentives influence financial market dynamics. Specifically, I estimate the impact of brown lending resistance, i.e., aggregate carbon preferences within each country, on carbon sensitivity of lending, i.e., the relative reduction in the international trade of brown loans by a country, on various aggregation levels.

The macro-level results provide evidence for compositional changes in aggregate loan portfolios towards cleaner sectors by more developed countries. This is shaped by multiple factors, including a lower propensity for society to be damaged by climate hazards, a better business environment to leverage market investments to transition actions and more pro-environmental preferences among the population.

The assessment of how divergent the international financial decarbonization and how relevant the international brown transfer has been provides important policy implications. A country-specific climate measure targeting all lenders and incomes from all destinations can theoretically remove this international transfer incentive, hence reducing the exposure of a country's banking system to climate risks. But it is impossible to attain in practice. Moreover, if climate-risky assets are concentrated in the financial institutions of more vulnerable countries, the vulnerable countries will become more vulnerable. When a crisis hits, the countries with low aggregate exposure can still receive adverse shocks subsequently due to financial contagion.

Exploiting share retention variations at the intensive margin, I then find a more active reduction of brown exposure by lenders that are from countries with higher resistance, that tend to retain shares on the balance sheet, and that are lead arrangers in term loans. In general, lead arrangers and other lenders show significant differences in their brown lending preferences. I further show that cross-border risk transfer in response to higher brown lending resistance is mainly through non-lead lenders in credit lines.

At the center of my analysis lie two types of risk transfers: from more regulated regions to less regulated regions and from more regulated lenders to less regulated lenders. These observations should raise regulatory concerns. The absence of exposure reduction in term loans by non-lead lenders possibly suggests the ease of transferring such risks to less-regulated lenders, especially in more developed countries. In the meantime, evidence of lenders using credit lines more to deal with brown borrowers suggests that lenders' climate risk management has been increasing. Nevertheless, this shows that, to a large extent, lenders prefer better contracting than leaving. One interpretation is that the lender's brown lending demand may not be sufficiently elastic due to low substitutability and/or diversification needs, where current financial regulations may also have a role (Gasparini et al., 2024).

Reducing exposure may not be feasible for all financial institutions. Given an inelastic exposure, financial institutions should monitor the probability of default more actively and engage more to prevent the default. They could also minimize potential loss given default with better contracting practices. In line with Brown et al. (2021), flexibility in contracting has shown to be increasingly valued by lenders as a tool of climate risk management, and the new trends may be of interest to financial regulators. A direct regulatory measure to reduce brown lending exposure is unlikely to be efficient.

With the last empirical exercise, I show that the ECB's attempt at climate banking supervision backfired due to its soft nature, lack of specific goals and enforcement, and inherent disparity. This expectation-based measure has unintentionally increased brown lending across all lenders within the European banking supervision framework, with a larger expansion observed among non-targeted financial institutions compared to the targeted ones. This could lead to misleading policy evaluations, as using non-targeted institutions as a benchmark may falsely suggest that the targeted group reduced their brown exposure. As an implication, cross-border alignment in climate-related financial regulations is essential for effective international cooperation in climate policy.

TABLE 1—SUMMARY STATISTICS FOR COUNTRY-LEVEL SAMPLES

Note: This table reports summary statistics for the country-level samples. Part A concerns the bilateral sample used in Columns 1 and 2 of Table 3. Part B concerns the sectoral exposure sample used in Columns 3-5 of Table 3, Table 4, Table 5, as well as Figure 2. The bilateral lending values are measured in millions of US dollars. The detailed variable definitions are in Table C1.

	N	Mean	S.D.	Min	Max
A. Bilateral lending					
Bilateral lending	452,352	136.00	2469.31	0	450,727.10
Bilateral lending, *foreign*	438,216	63.83	629.86	0	54,740.05
Log GDP per capita	452,352	10.07	1.12	6.09	11.68
EI	452,352	0.76	1.51	0	7.26
B. Sectoral weight					
Sectoral weight (%), *total*	6,424	7.05	8.47	0	78.48
Sectoral weight (%), *domestic*	6,424	7.47	10.71	0	93.83
Sectoral weight (%), *foreign*	6,424	6.85	8.51	0	75.53
Log GDP per capita	6,424	10.28	0.95	6.09	11.60
EI	6,424	0.78	1.53	0	7.26

TABLE 2—SUMMARY STATISTICS FOR LENDER-LOAN LEVEL SAMPLES

Note: This table summarizes the lender-level samples. Panel A summarizes the lender-loan sample used in Table 6, Table 7, and Table 8. Panel B summarizes the parent lender-loan sample used in Table 9 and Table 10. Panel C summarizes the lender-year-level sample used in Table 11. All sectoral exposures at the lender-year level are measured in millions of US dollars. The detailed variable definitions are in Table C1.

	N	Mean	S.D.	Min	Max
A. Lender-loan sample					
Share in a facility (%), *by each direct lender*	60,384	10.64	16.03	0.00	100.00
EIR	60,384	0.42	0.98	0.00	5.62
Log GDP per capita	60,384	10.51	0.60	6.15	11.80
Foreign	60,384	0.50	0.50	0	1
B. Parent-lender-loan sample					
Total share in a loan facility (%), *by each parent lender*	397,487	17.41	20.97	0.00	100.19
EIR	58,000	0.41	0.98	0.00	5.62
EI	397,487	0.85	1.58	0.00	7.26
Log GDP per capita	397,487	10.20	0.81	5.38	11.80
Foreign	397,487	0.48	0.50	0	1
RCA, based on reported shares	327,749	1.80	15.28	0.00	6595.17
RCA, based on approximated shares	336,831	1.62	4.22	0.00	1011.07
C. Lender-year sample					
Reported sectoral loans, total	34,483	19.86	59.09	0.00	2069.20
Reported sectoral loans, domestic	17,409	10.24	49.55	0.00	1805.68
Reported sectoral loans, foreign	17,409	18.37	48.84	0.00	1136.37
EI	34,483	0.66	1.24	0.00	6.22
SI	34,483	0.15	0.36	0	1
Post Guide	34,483	0.42	0.49	0	1
Other SSM-related lender	34,483	0.04	0.20	0	1
SSM Lenders					
SI	6477	0.79	0.41	0	1
Reported sectoral loans, total	6477	19.64	51.09	0.01	1345.84
Reported sectoral loans, domestic	4063	5.41	30.14	0.00	1310.65
Reported sectoral loans, foreign	4063	21.16	49.32	0.01	970.94

TABLE 3—SECTORAL RECOMPOSITION: COUNTRY-LEVEL EVIDENCE

Note: This table reports the country-level estimation results. Columns 1 and 2 report the PPML estimates from Equation 4, with the dependent variable being the yearly and sector-specific bilateral lending flows. Column 1 includes domestic lending, while Column 2 excludes the domestic flows. Standard errors are clustered at the original country, lender country, and year levels. Columns 3 to 5 report the HDFE estimates from Equation 5, considering the lenders with nonzero lending for more than 12 out of 24 years. The dependent variables are the value weights of sectoral loans in a country's lending portfolios, concerning the total, domestic, and foreign portfolios, respectively. Domestic loans require the borrower country to be the same as the reported lender operating countries. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. Standard errors are clustered at the sector and country levels. EI stands for sectoral emission intensity. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Bilateral Lending		Sectoral Weight (%)		
	(1)	(2)	(3)	(4)	(5)
	Total	Foreign	Total	Domestic	Foreign
EI X Log GDP per capita	-0.056***	-0.030	-0.492***	-0.675***	-0.065
	(0.018)	(0.021)	(0.137)	(0.079)	(0.144)
Constant	13.946***	12.232***	11.002***	12.891***	7.381***
	(0.137)	(0.178)	(1.096)	(0.636)	(1.157)
N	452352	438216	6424	6424	6424
Pseudo / Adjusted R2	0.952	0.894	0.802	0.601	0.798

TABLE 4—ADDITIONAL CONTROLS FOR BROWN LENDING RESISTANCE

Note: This table reports the HDFE estimates from Equation 5 after including various sets of controls. The dependent variable is the value weight of sectoral loans in a country's total lending portfolios. Standard errors are clustered at the sector and country levels. Column 1 additionally controls for interaction terms with bank deposits to GDP, bank concentration (asset share of the three largest commercial banks), bank non-performing loans to gross loans, bank net interest margin, and bank regulatory capital to risk-weighted assets. Column 2 additionally includes the interactions with financial system deposits to GDP, mutual fund assets to GDP, total value of stock traded to GDP, corporate bond issuance volume to GDP, pension fund assets to GDP, foreign claims to GDP, and syndicated loan issuance volume to GDP. Column 3 additionally includes the interactions with heating degree days, the renewable energy share in consumption, and the trade of environmental goods. Column 4 comprises all of the additional interaction terms. Column 5 comprises the previously significant additions involving bank concentration, syndicated loan issuance volume to GDP, and heating degree days. The additional controls chosen have a moderate correlation (between ± 0.15 and ± 0.5) with log GDP per capita. EI stands for sectoral emission intensity. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Sectoral Weight (%)				
	(1)	(2)	(3)	(4)	(5)
EI X Log GDP per capita	-0.451***	-0.693***	-0.374**	-0.576***	-0.322***
	(0.085)	(0.177)	(0.176)	(0.140)	(0.073)
Constant	11.574***	12.959***	10.318***	10.927***	10.391***
	(0.730)	(1.355)	(1.779)	(1.133)	(0.742)
Controls	Bank profitability & risk-taking	Financial development	Energy demand & preferences	All	Selected
N	4445	4208	5075	3718	5071
Adjusted R2	0.785	0.801	0.790	0.798	0.799

TABLE 5—DECOMPOSING ECONOMIC DEVELOPMENT: MECHANISM TESTS

Note: This table reports the HDFE estimates from Equation 5 with alternative proxies for brown lending resistance. The dependent variable is the value weight of sectoral loans in a country's total lending portfolios. Standard errors are clustered at the sector and country levels. EI stands for sectoral emission intensity. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Columns 1 to 4 additionally include the interaction term with the GAIN index, Readiness index, Vulnerability index, and Self-expression score, respectively. Column 5 simultaneously includes the Readiness index, Vulnerability index, and Self-expression score. The added variables are highly correlated with log GDP per capita (between ± 0.7 and ± 0.9). The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Sectoral Weight (%)				
	(1)	(2)	(3)	(4)	(5)
EI X Log GDP per capita	-0.130	-0.334**	-0.161*	-0.203***	0.195
	(0.128)	(0.136)	(0.076)	(0.056)	(0.225)
EI X GAIN	-0.105***				
	(0.027)				
EI X Readiness		-4.455***			-4.108***
		(1.345)			(1.015)
EI X Vulnerability			11.102***		12.664***
			(2.815)		(3.847)
EI X Self-Expression				-0.575***	-0.275
				(0.167)	(0.276)
Constant	13.343***	11.837***	5.329***	9.157***	4.283*
	(1.370)	(1.311)	(1.079)	(0.589)	(2.269)
N	5886	5886	5886	6147	5609
Adjusted R2	0.796	0.796	0.796	0.809	0.805

TABLE 6—LOAN-LEVEL REALLOCATION AND POTENTIAL SELLOFFS

Note: This table reports the HDFE estimates from Equation 6 with the full sample in Column 1 and subsamples with small share lenders in Columns 2 to 5. Standard errors are clustered at the borrower level. Small share lenders refer to lenders with a retained share below 30%. Specifically, Column 3 excludes Term B loans. Column 4 concerns credit line loans, and Column 5 concerns Term A loans. The dependent variable is the share (%) of contribution to a loan facility (tranche) by each lender. EIR stands for emission intensity based on revenue at the firm-year level. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	All lenders	Small share lenders	Small share lenders		
	(1)	(2)	(3)	(4)	(5)
			all excl. Term B	*Credit Line*	*Term A*
Panel A: Share in a loan facility (%), all loans					
EIR X Log GDP per capita	-0.328**	-0.233***	-0.232***	-0.275***	0.140
	(0.146)	(0.057)	(0.057)	(0.083)	(0.273)
Constant	10.142***	8.206***	8.214***	8.179***	6.051***
	(0.633)	(0.247)	(0.245)	(0.385)	(0.744)
N	60384	56660	56134	32504	2233
Adjusted R2	0.769	0.713	0.713	0.750	0.728
Panel B: Share in a loan facility (%), foreign loans					
EIR X Log GDP per capita	-0.166*	-0.189***	-0.188***	-0.177*	0.535*
	(0.085)	(0.072)	(0.072)	(0.099)	(0.276)
Constant	7.719***	7.084***	7.086***	6.696***	3.157***
	(0.388)	(0.327)	(0.325)	(0.487)	(0.955)
N	30232	28902	28698	16023	909
Adjusted R2	0.775	0.744	0.744	0.774	0.733

TABLE 7—SYNDICATE ROLE HETEROGENEITY

Note: This table reports the HDFE estimates from the appended version of Equation 6. Column 1 estimates the equation as follows:

$$\begin{aligned}\text{Loan share}_{lbt} = \alpha + \beta EIR_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_1 Agent_{lbt} + \lambda_2 Agent_{lbt} \times EIR_{bt-1} \\ + \lambda_3 Agent_{lbt} \times \log(\text{GDP per capita})_{lt-1} + \lambda_4 Agent_{lbt} \times EIR \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt}.\end{aligned}$$

Columns 2 to 4 estimate the equation appended with *Lead Arranger* instead of *Agent*. In Column 5, I estimate the following equation on the subsample of lead arrangers:

$$\begin{aligned}\text{Loan share}_{lbt} = \alpha + \beta EIR_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_1 Term\ Loan_{bt} \times \log(\text{GDP per capita})_{lt-1} \\ + \lambda_2 Term\ Loan_{bt} \times EIR \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt}.\end{aligned}$$

l indicates lender, b for the loan and t for the year. Standard errors are clustered at the borrower level. The dependent variable is the share (%) of contribution to a loan facility (tranche) by each lender. EIR stands for emission intensity based on revenue at the firm-year level. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Agent refers to the lenders participating in the underwriting process, and lead arrangers are the lead agents of syndication. Term loans comprise all types of term loans. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	All lenders	All agents	All lenders		Lead arrangers
	(1)	(2)	(3)	(4)	(5)
			Credit Line	*Term Loan*	
EIR X Log GDP per capita	-0.323**	-0.098	-0.286***	0.100	-0.779*
	(0.161)	(0.138)	(0.096)	(0.302)	(0.407)
Agent	13.974***				
	(2.532)				
Agent X EIR	-1.462				
	(2.736)				
Agent X Log GDP per capita	-0.996***				
	(0.238)				
Agent X EIR X Log GDP per capita	0.121				
	(0.258)				
Lead arranger		3.300	10.401**	-6.115	
		(4.867)	(4.757)	(5.024)	
Lead arranger X EIR		9.736**	-2.380	12.473***	
		(4.783)	(2.770)	(4.547)	
Lead arranger X Log GDP per capita		-0.279	-0.741*	0.735	
		(0.461)	(0.440)	(0.473)	
Lead arranger X EIR X Log GDP per capita		-0.937**	0.193	-1.182***	
		(0.451)	(0.258)	(0.421)	
Term loan X Log GDP per capita					0.497*
					(0.263)
Term loan X EIR X Log GDP per capita					-1.313***
					(0.463)
Constant	8.505***	10.677***	8.702***	8.990***	15.272***
	(0.702)	(0.613)	(0.446)	(1.202)	(1.954)
N	60384	27770	33624	23266	16217
Adjusted R2	0.782	0.820	0.789	0.762	0.896

TABLE 8—FOREIGN LEAD ARRANGER ACTIVITIES

Note: This table reports the HDFE estimates from the appended version of Equation 6 as follows:

$$\text{Loan share}_{lbt} = \alpha + \beta EIR_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_1 Foreign_{lbt} + \lambda_2 Foreign_{lbt} \times EIR_{bt-1}$$
$$+ \lambda_3 Foreign_{lbt} \times \log(\text{GDP per capita})_{lt-1} + \lambda_4 Foreign_{lbt} \times EIR \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt},$$

where l indexes direct lenders, b indexes loan and t indexes year. Standard errors are clustered at the borrower level. The dependent variable is the share (%) of contribution to a loan facility (tranche) by each lender. EIR stands for emission intensity based on revenue at the firm-year level. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. Lead stands for Lead arrangers, i.e. the lead agents of syndication, and Other stands for the other lenders. Term loans comprise all types of term loans. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Lead rrangers	Credit Line			Term Loan		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		All	*Lead*	*Other*	*All*	*Lead*	*Other*
EIR X	-1.779***	-1.044***	0.165	-0.846***	-0.298	-2.885***	0.272
Log GDP per capita	(0.412)	(0.329)	(0.401)	(0.274)	(0.425)	(0.341)	(0.330)
Foreign	-14.805	-12.444**	-3.651	-10.135*	-25.004***	-15.703	-24.595***
	(9.479)	(5.849)	(8.170)	(5.993)	(7.078)	(18.907)	(8.068)
Foreign X EIR	-5.619	-8.535**	1.263	-6.683**	-4.007	-3.809	4.579
	(6.443)	(3.430)	(5.231)	(2.863)	(5.664)	(15.800)	(3.973)
Foreign X	1.302	0.927*	0.217	0.751	2.074***	1.265	2.027***
Log GDP per capita	(0.897)	(0.549)	(0.779)	(0.564)	(0.669)	(1.795)	(0.763)
Foreign X EIR X	0.559	0.808**	-0.073	0.626**	0.381	0.523	-0.419
Log GDP per capita	(0.609)	(0.317)	(0.491)	(0.265)	(0.534)	(1.510)	(0.372)
Constant	19.937***	14.048***	10.981***	11.378***	12.859***	25.121***	8.080***
	(1.729)	(1.528)	(1.873)	(1.287)	(1.701)	(1.349)	(1.332)
N	10046	30249	4087	23271	18536	4063	11907
Adjusted R2	0.896	0.787	0.889	0.743	0.764	0.903	0.692

TABLE 9—LENDER PARENT HETEROGENEITY

Note: This table reports the HDFE estimates from Equation 6 with the parent lender-loan-level samples. The dependent variable is the total share (%) of contribution to a loan facility (tranche) by each parent lender. Standard errors are clustered at the borrower level. Column 1 uses the full sample. Columns 2 and 3 contrast parent lenders that are identified as banks with those that are not. Columns 4 and 5 contrast parent lenders that are weak with those that are not. Weak lenders are those whose Tier 1 capital ratio is within the bottom 25% percentiles. EIR stands for emission intensity based on revenue at the firm-year level. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	All lenders	Banks	Non-banks	Weak	Non-weak
	(1)	(2)	(3)	(4)	(5)
Panel A: Total share in a loan facility (%), all loans					
EIR X Log GDP per capita	-0.288**	-0.237*	-0.224	-0.329***	-0.466**
	(0.141)	(0.123)	(0.300)	(0.087)	(0.207)
Constant	10.313***	9.781***	9.180***	10.223***	11.008***
	(0.607)	(0.500)	(1.483)	(0.382)	(0.760)
N	58000	42974	6856	8325	20190
Adjusted R2	0.741	0.727	0.672	0.785	0.736
Panel B: Total share in a loan facility (%), foreign loans					
EIR X Log GDP per capita	-0.152**	-0.223***	-0.188	-0.391***	-0.060
	(0.066)	(0.078)	(0.470)	(0.072)	(0.122)
Constant	7.975***	8.272***	7.766***	8.104***	8.252***
	(0.292)	(0.319)	(2.834)	(0.338)	(0.437)
N	33269	25746	2632	5138	13629
Adjusted R2	0.745	0.731	0.693	0.728	0.725

TABLE 10—SECTORAL EXPOSURE AND RELATIVE COMPARATIVE ADVANTAGE

Note: This table reports the HDFE estimates from Equation 7. Standard errors are clustered at the borrower level. The dependent variable is the total share (%) of contribution to a loan facility (tranche) by each parent lender. EI stands for sectoral emission intensity. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. RCA stands for the Relative Comparative Advantage measure, constructed as the weight of a sector in the given bank's portfolio relative to that in the world portfolio. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Total share in a loan facility (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
	All loans	Foreign loans	All loans	Foreign loans	All loans	Foreign loans
EI X Log GDP per capita	-0.095*** (0.031)	-0.051* (0.030)	-0.122*** (0.037)	-0.091*** (0.034)	-0.105*** (0.037)	-0.110*** (0.035)
RCA			0.407* (0.235)	0.498** (0.230)	0.516*** (0.198)	0.737*** (0.180)
EI X RCA			-0.131* (0.073)	-0.216*** (0.065)	-0.095 (0.099)	-0.339*** (0.098)
Log GDP per capita X RCA			-0.033 (0.022)	-0.037 (0.024)	-0.038* (0.019)	-0.060*** (0.018)
EI X Log GDP per capita X RCA			0.013* (0.008)	0.022*** (0.007)	0.013 (0.010)	0.035*** (0.011)
Constant	15.313*** (0.258)	10.988*** (0.267)	15.708*** (0.309)	11.509*** (0.314)	15.503*** (0.309)	11.704*** (0.319)
RCA measure	*No*		*Based on the reported shares*		*Based on the predicted shares*	
N	397487	190966	327749	156767	336832	160210
Adjusted R2	0.717	0.750	0.709	0.751	0.711	0.753

TABLE 11—SUPERVISORY PRESSURE AND SECTORAL EXPOSURE ADJUSTMENT

Note: This table reports the HDFE estimates from Equations 8 and 9. Standard errors are clustered at the sector and lender levels. The dependent variable is the loan amount by a direct lender to each sector in a year, computed on the reported shares, with Columns 1 and 4 considering total loans, Columns 2 and 5 considering domestic loans, and Columns 3 and 6 considering foreign loans. Domestic loans require the borrower country to be the same as the reported lender operating countries. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. EI stands for sectoral emission intensity. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. The dummy *SI* directly indicates whether a lending institution is classified as an SI either at the subsidiary or parent levels during a given year. The dummy $Other\ SSM-related\ lender$ takes one if a lender or its parent (both not SI) is from the SSM area during a given year and zero otherwise. The control group is thus the non-SI lenders that operate in the non-SSM area at both the direct and parent levels. The SSM area covers Belgium, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Austria, Portugal, Slovenia, Slovakia, Finland, Estonia, Bulgaria (since 2020), and Croatia (since 2020). The sample covers 2015 to 2023, and the dummy variable $PostGuide$ takes one for years since 2020 and zero otherwise. I exclude the lenders with less than five years of lending (to any sector) from the sample. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Reported sectoral loans					
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Domestic	Foreign	Total	Domestic	Foreign
EI X Log GDP per capita				-1.991***	-5.768***	-0.436
				(0.574)	(1.604)	(1.193)
EI X SI	-0.818	-0.870	-1.100	1.303	1.288	2.169***
	(0.884)	(0.859)	(1.443)	(1.428)	(1.385)	(0.735)
Post Guide X EI X SI	-11.739**	-13.899**	-6.587	4.783***	2.934***	3.142***
	(4.351)	(6.030)	(4.241)	(0.976)	(0.962)	(0.968)
EI X Other SSM-related lender				1.704	2.280	3.047
				(1.884)	(1.387)	(1.787)
Post Guide X EI X Other SSM-related lender				16.075***	14.810**	9.657**
				(4.717)	(6.594)	(4.531)
Constant	24.806***	10.100***	26.273***	34.362***	51.887***	22.725**
	(0.863)	(1.256)	(0.404)	(3.746)	(11.388)	(8.401)
SSM lenders only		Y			N	
N	6477	4063	4063	34483	17409	17409
Adjusted R2	0.147	0.036	0.179	0.184	0.210	0.246

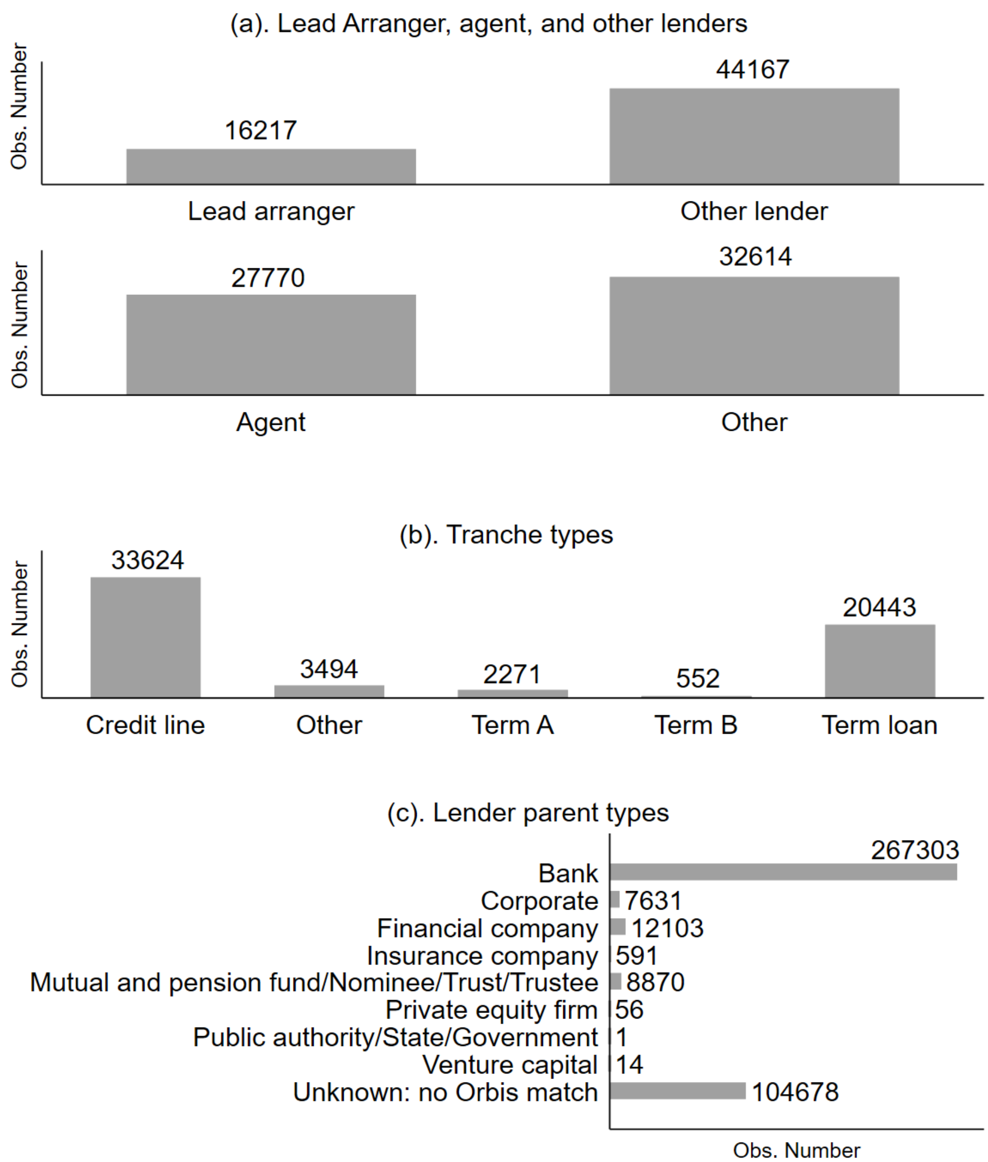

FIGURE 1. SUMMARY OF LENDER ROLES AND LOAN TYPES

This figure summarizes the sample composition. Part (a) shows how the lender-loan-level sample can be split by lender roles. Part (b) shows the representation of the main tranche types, with credit lines being the most important type. Part (c) shows the sample distribution across the lender parent types. This figure presents the lender and loan heterogeneity in the lender-loan level sample.

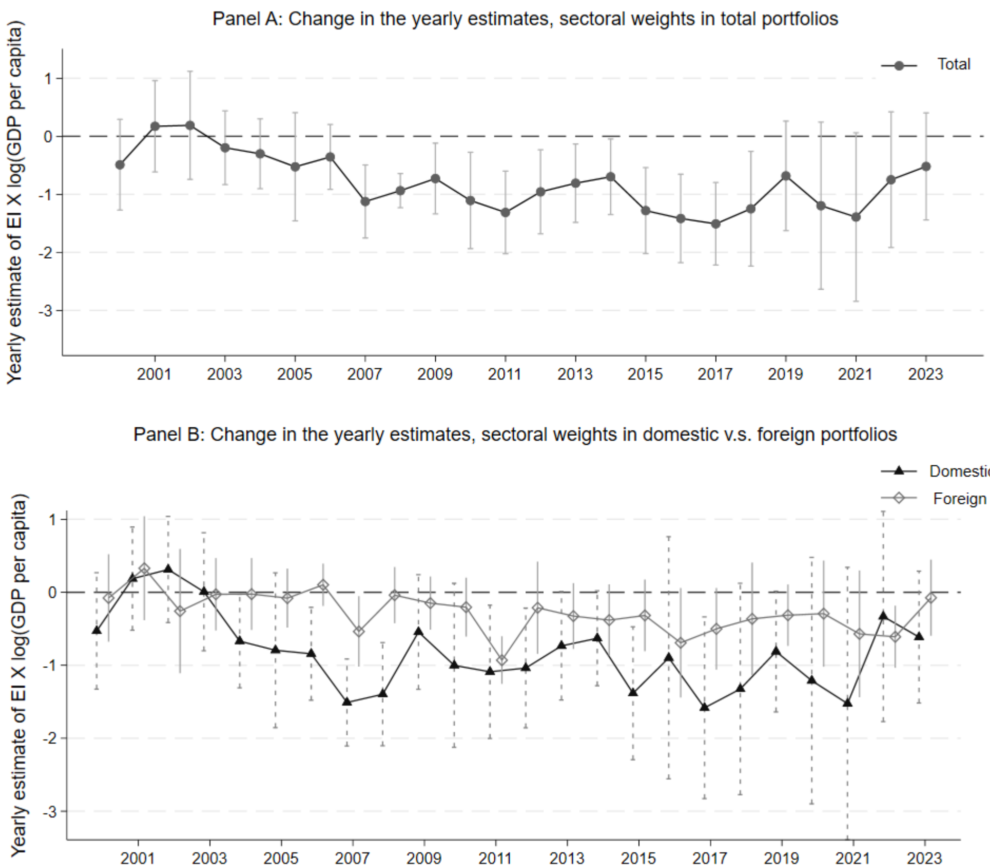

FIGURE 2. ESTIMATES WITH PORTFOLIO WEIGHTS OVER 2001 - 2023

This figure presents the yearly evolution of the estimated relationship between the carbon sensitivity of lending and the GDP per capita. The yearly HDFE estimates are obtained using the equation below:

$$\text{Sectoral weight}_{lKt} = \alpha + \sum_{t=2000}^{t=2023} \beta_t \, EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} \times I_t + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}.$$

where l indicates lender, K for the sector and t for the year. Standard errors are clustered at the sector level. The plotted estimates show the evolution of β_t, i.e., how the relationship between the carbon sensitivity of lending and GDP per capita changed from 2000 to 2023. Panel A considers the total portfolios and Panel B contrasts the results for domestic and foreign portfolios. The detailed variable definitions are in Table C1. The plotted confidence interval is at the 95% level.

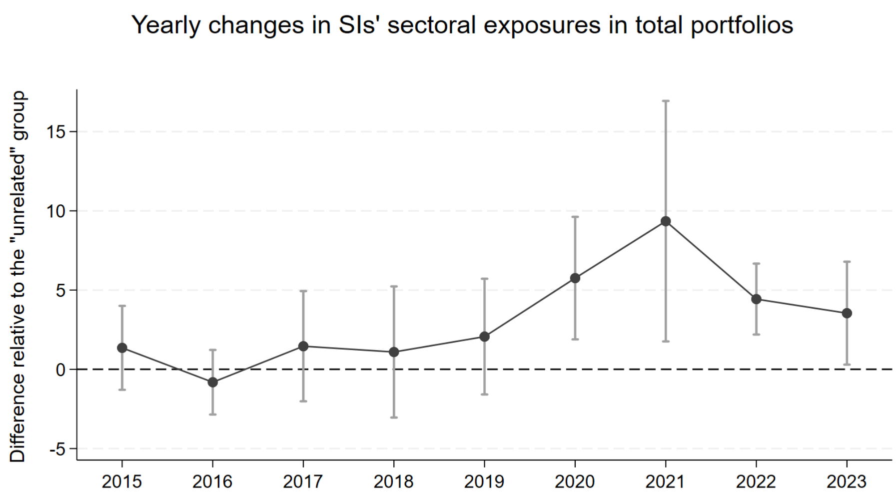

FIGURE 3. ESTIMATES WITH SIS' SECTORAL EXPOSURES OVER 2015 - 2023

This figure describes how the carbon sensitivity based on the sectoral exposures of the significant institutions (SI) changes over time relative to the control group of "unrelated" lenders. The yearly HDFE estimates are obtained using the equation below:

$$\text{Sectoral Exposure}_{lKt} = \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} + \sum_{t=2015}^{t=2023} \gamma_t \ EI_{Kt-1} \times SI_{lt} \times I_t$$
$$+ \sum_{t=2015}^{t=2023} \theta_t \ EI_{Kt-1} \times Other\ SSM-related\ Lender_{lt} \times I_t + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}.$$

where l indicates lender, b for the loan and t for the year. Standard errors are clustered at the sector and lender level. The control group consists of lenders who are not significant institutions or other SSM-related lenders. The base estimates $EI_{Kt-1} \times I_t$ are absorbed by the fixed effects λ_{Kt}. The plotted estimates show the evolution of γ_t, i.e., how the sectoral exposure of SIs changes over time relative to the "unrelated" lenders. Before the introduction of the Guide in 2020, there were no significant differences between the two groups. Since 2020, the directly supervised SIs showed an initial increase in their carbon sensitivity of lending. The response faded through the following years. Figure C1 shows the estimates regarding the non-SI SSM lenders compared to the "unrelated" lenders. Figure C2 compares the results using the two different control groups — the non-SI SSM lenders versus the "unrelated" lenders. The detailed variable definitions are in Table C1. The plotted confidence interval is at the 95% level.

References

Aiello, M. A. (2024). Climate supervisory shocks and bank lending: Empirical evidence from microdata. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4756516

Aiyar, S., Calomiris, C. W., & Wieladek, T. (2014). Does Macro-Prudential Regulation Leak? Evidence from a UK Policy Experiment. *Journal of Money, Credit and Banking*, *46*(s1), 181–214. https://doi.org/10.1111/jmcb.12086

Aviat, A., & Coeurdacier, N. (2007). The geography of trade in goods and asset holdings. *Journal of International Economics*, *71*(1), 22–51. https://doi.org/10.1016/j.jinteco.2006.02.002

Babiker, M. H. (2005). Climate change policy, market structure, and carbon leakage. *Journal of International Economics*, *65*(2), 421–445. https://doi.org/10.1016/j.jinteco.2004.01.003

Bae, S. C., Chang, K., & Yi, H.-C. (2018). Corporate social responsibility, credit rating, and private debt contracting: New evidence from syndicated loan market. *Review of Quantitative Finance and Accounting*, *50*(1), 261–299. https://doi.org/10.1007/s11156-017-0630-4

Beck, T. (2002). Financial development and international trade. *Journal of International Economics*, *57*(1), 107–131. https://doi.org/10.1016/S0022-1996(01)00131-3

Beck, T., Ioannidou, V., & Schäfer, L. (2018). Foreigners vs. Natives: Bank Lending Technologies and Loan Pricing. *Management Science*, *64*(8), 3792–3820. https://doi.org/10.1287/mnsc.2016.2706

Beck, T., Levine, R., & Loayza, N. (2000). Finance and the sources of growth. *Journal of Financial Economics*, *58*(1-2), 261–300. https://doi.org/10.1016/S0304-405X(00)00072-6

Benincasa, E., Kabas, G., & Ongena, S. R. G. (2022). "There is No Planet B", but for Banks "There are Countries B to Z": Domestic Climate Policy and Cross-Border Bank Lending. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4075737

Benink, H., Huizinga, H., Raes, L., & Zhang, L. (2024). International Trade in Brown Shares and Economic Development. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4703966

Blickle, K., Fleckenstein, Q., Hillenbrand, S., & Saunders, A. (2020). The Myth of the Lead Arranger's Share. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3594525

Blickle, K., Parlatore, C., & Saunders, A. (2023, March). *Specialization in Banking* (tech. rep. No. w31077). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w31077

Bolton, P., & Kacperczyk, M. (2021, February). *Global Pricing of Carbon-Transition Risk* (tech. rep. No. w28510). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w28510

Bolton, P., & Kacperczyk, M. (2023). Global Pricing of Carbon-Transition Risk. *The Journal of Finance*, *78*(6), 3677–3754. https://doi.org/10.1111/jofi.13272

Bowen, A., Cochrane, S., & Fankhauser, S. (2012). Climate change, adaptation and economic growth. *Climatic Change*, *113*(2), 95–106. https://doi.org/10.1007/s10584-011-0346-8

Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering Cash Flow Shocks. *The Journal of Finance*, *76*(4), 1731–1772. https://doi.org/10.1111/jofi.13024

Bruche, M., Malherbe, F., & Meisenzahl, R. R. (2020). Pipeline Risk in Leveraged Loan Syndication (P. Strahan, Ed.). *The Review of Financial Studies*, *33*(12), 5660–5705. https://doi.org/10.1093/rfs/hhaa029

Bruno, B., & Lombini, S. (2023). Climate transition risk and bank lending. *Journal of Financial Research*, *46*(S1). https://doi.org/10.1111/jfir.12360

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, *130*(3), 453–483. https://doi.org/10.1016/j.jfineco.2018.03.011

Chakraborty, I., Goldstein, I., & MacKinlay, A. (2018). Housing Price Booms and Crowding-Out Effects in Bank Lending. *The Review of Financial Studies*, *31*(7), 2806–2853. https://doi.org/10.1093/rfs/hhy033

Chava, S. (2014). Environmental Externalities and Cost of Capital. *Management Science*, *60*(9), 2223–2247. https://doi.org/10.1287/mnsc.2013.1863

Chu, Y., Xiao, Z., & Zheng, Y. (2021). The Industry Expertise Channel of Mortgage Lending. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3792629

Chu, Y., Zhang, D., & Zhao, Y. ((2019). Bank Capital and Lending: Evidence from Syndicated Loans. *Journal of Financial and Quantitative Analysis*, *54*(2), 667–694. https://doi.org/10.1017/S0022109018000698

Correia, S. (2017). Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator. *Working Paper*.

De Haas, R. (2023). Sustainable Banking. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4620166

De Haas, R., & Popov, A. (2023). Finance and Green Growth. *The Economic Journal*, *133*(650), 637–668. https://doi.org/10.1093/ej/ueac081

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., & Stantcheva, S. (2022, July). *Fighting Climate Change: International Attitudes Toward Climate Policies* (tech. rep. No. w30265). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w30265

Degryse, H., Goncharenko, R., Theunisz, C., & Vadasz, T. (2023). When green meets green. *Journal of Corporate Finance*, *78*, 102355. https://doi.org/10.1016/j.jcorpfin.2023.102355

Deidda, L., & Fattouh, B. (2008). Banks, financial markets and growth. *Journal of Financial Intermediation*, *17*(1), 6–36. https://doi.org/10.1016/j.jfi.2006.04.003

Delis, M. D., Greiff, K. D., Iosifidi, M., & Ongena, S. (2024). Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans. *Financial Markets, Institutions & Instruments*, fmii.12189. https://doi.org/10.1111/fmii.12189

Demirgüç-Kunt, A., Pedraza, A., Pulga, F., & Ruiz-Ortega, C. (2024). Global Bank Lending Under Climate Policy. *IMF Economic Review*, *72*(2), 858–901. https://doi.org/10.1057/s41308-023-00217-8

Demiroglu, C., & James, C. (2015). Bank loans and troubled debt restructurings. *Journal of Financial Economics*, *118*(1), 192–210. https://doi.org/10.1016/j.jfineco.2015.01.005

Dennis, S. A., & Mullineaux, D. J. (2000). Syndicated Loans. *Journal of Financial Intermediation*, *9*(4), 404–426. https://doi.org/10.1006/jfin.2000.0298

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics*, *131*(3), 693–714. https://doi.org/10.1016/j.jfineco.2018.08.013

Ehlers, T., Packer, F., & De Greiff, K. (2022). The pricing of carbon risk in syndicated loans: Which risks are priced and why? *Journal of Banking & Finance*, *136*, 106180. https://doi.org/10.1016/j.jbankfin.2021.106180

Faiella, I., & Natoli, F. (2018, October). Natural Catastrophes and Bank Lending: The Case of Flood Risk in Italy. https://doi.org/10.2139/ssrn.3429210

Fan, H., Peng, Y., Wang, H., & Xu, Z. (2021). Greening through finance? *Journal of Development Economics*, *152*, 102683. https://doi.org/10.1016/j.jdeveco.2021.102683

Filippini, M., Leippold, M., & Wekhof, T. (2024). Sustainable finance literacy and the determinants of sustainable investing. *Journal of Banking & Finance*, *163*, 107167. https://doi.org/10.1016/j.jbankfin.2024.107167

Fisman, R., & Love, I. (2007). Financial Dependence and Growth Revisited. *Journal of the European Economic Association*, *5*(2-3), 470–479. https://doi.org/10.1162/jeea.2007.5.2-3.470

Gantchev, N., Giannetti, M., & Li, R. (2022). Does Money Talk? Divestitures and Corporate Environmental and Social Policies. *Review of Finance*, *26*(6), 1469–1508. https://doi.org/10.1093/rof/rfac029

Gasparini, M., Ives, M. C., Carr, B., Fry, S., & Beinhocker, E. (2024). Model-based financial regulations impair the transition to net-zero carbon emissions. *Nature Climate Change*. https://doi.org/10.1038/s41558-024-01972-w

Giannetti, M., & Laeven, L. (2012). The flight home effect: Evidence from the syndicated loan market during financial crises. *Journal of Financial Economics*, *104*(1), 23–43. https://doi.org/10.1016/j.jfineco.2011.12.006

Ginglinger, E., & Moreau, Q. (2023). Climate Risk and Capital Structure. *Management Science*, *69*(12), 7492–7516. https://doi.org/10.1287/mnsc.2023.4952

Giometti, M., Güler, O., & Pietrosanti, S. (2024). Bank Specialization, Control Rights, and Real Effects. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4873446

Goss, A., & Roberts, G. S. (2011). The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance*, *35*(7), 1794–1810. https://doi.org/10.1016/j.jbankfin.2010.12.002

Gu, G. W., & Hale, G. (2023). Climate risks and FDI. *Journal of International Economics*, *146*, 103731. https://doi.org/10.1016/j.jinteco.2023.103731

Haselmann, R., & Wachtel, P. (2011). Foreign banks in syndicated loan markets. *Journal of Banking & Finance*, *35*(10), 2679–2689. https://doi.org/10.1016/j.jbankfin.2011.02.023

Ho, K., & Wong, A. (2023). Effect of climate-related risk on the costs of bank loans: Evidence from syndicated loan markets in emerging economies. *Emerging Markets Review*, *55*, 100977. https://doi.org/10.1016/j.ememar.2022.100977

Houston, J. F., & Shan, H. (2022). Corporate ESG Profiles and Banking Relationships (P. Strahan, Ed.). *The Review of Financial Studies*, *35*(7), 3373–3417. https://doi.org/10.1093/rfs/hhab125

Irani, R. M., Iyer, R., Meisenzahl, R. R., & Peydró, J.-L. (2021). The Rise of Shadow Banking: Evidence from Capital Regulation (F. Cornelli, Ed.). *The Review of Financial Studies*, *34*(5), 2181–2235. https://doi.org/10.1093/rfs/hhaa106

Ivanov, I. T., Kruttli, M. S., & Watugala, S. W. (2023). Banking on Carbon: Corporate Lending and Cap-and-Trade Policy (R. Koijen, Ed.). *The Review of Financial Studies*, hhad085. https://doi.org/10.1093/rfs/hhad085

Ivashina, V., & Scharfstein, D. (2010). Loan Syndication and Credit Cycles. *American Economic Review*, *100*(2), 57–61. https://doi.org/10.1257/aer.100.2.57

Ivashina, V., & Sun, Z. (2011). Institutional demand pressure and the cost of corporate loans73. *Journal of Financial Economics*, *99*(3), 500–522. https://doi.org/10.1016/j.jfineco.2010.10.009

Javadi, S., & Masum, A.-A. (2021). The impact of climate change on the cost of bank loans. *Journal of Corporate Finance*, *69*, 102019. https://doi.org/10.1016/j.jcorpfin.2021.102019

Jung, H., Santos, J. A. C., & Seltzer, L. (2023). U.S. Banks' Exposures to Climate Transition Risks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4411661

Kacperczyk, M. T., & Peydro, J.-L. (2021). Carbon Emissions and the Bank-Lending Channel. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3915486

LaCour-Little, M., Pavlov, A., & Wachter, S. (2024). Adverse Selection and Climate Risk: A Response to (M. Gregor, Ed.). *The Review of Financial Studies*, *37*(6), 1831–1847. https://doi.org/10.1093/rfs/hhad072

Laeven, L., & Popov, A. (2023). Carbon taxes and the geography of fossil lending. *Journal of International Economics*, *144*, 103797. https://doi.org/10.1016/j.jinteco.2023.103797

Martini, F., Sautner, Z., Steffen, S., & Theunisz, C. (2023). Climate Transition Risks of Banks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4551735

Meisenzahl, R. (2023). How Climate Change Shapes Bank Lending: Evidence from Portfolio Reallocation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4405234

Miguel, F., Pedraza, A., & Ruiz-Ortega, C. (2024). Climate-change regulations: Bank lending and real effects. *Journal of Financial Stability*, *70*, 101212. https://doi.org/10.1016/j.jfs.2023.101212

Nadauld, T. D., & Weisbach, M. S. (2012). Did securitization affect the cost of corporate debt? *Journal of Financial Economics*, *105*(2), 332–352. https://doi.org/10.1016/j.jfineco.2012.03.002

Nguyen, Q., Diaz-Rainey, I., Kuruppuarachchi, D., McCarten, M., & Tan, E. K. (2023). Climate transition risk in U.S. loan portfolios: Are all banks the same? *International Review of Financial Analysis*, *85*, 102401. https://doi.org/10.1016/j.irfa.2022.102401

Oehmke, M., & Opp, M. M. (2022). Green Capital Requirements. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4040098

Ouazad, A., & Kahn, M. E. (2022). Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters (S. Van Nieuwerburgh, Ed.). *The Review of Financial Studies*, *35*(8), 3617–3665. https://doi.org/10.1093/rfs/hhab124

Paravisini, D., Rappoport, V., & Schnabl, P. (2023). Specialization in Bank Lending: Evidence from Exporting Firms. *The Journal of Finance*, *78*(4), 2049–2085. https://doi.org/10.1111/jofi.13254

Petersen, M. A., & Rajan, R. G. (1995). The Effect of Credit Market Competition on Lending Relationships. *The Quarterly Journal of Economics*, *110*(2), 407–443. https://doi.org/10.2307/2118445

Reghezza, A., Altunbas, Y., Marques-Ibanez, D., Rodriguez d'Acri, C., & Spaggiari, M. (2022). Do banks fuel climate change? *Journal of Financial Stability*, *62*, 101049. https://doi.org/10.1016/j.jfs.2022.101049

Silva, J. M. C. S., & Tenreyro, S. (2006). The Log of Gravity. *The Review of Economics and Statistics*, *88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Simons, K. (1993). Why do banks syndicate loans? *New England Economic Review*, (Jan), 45–52.

Sufi, A. (2007). Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans. *The Journal of Finance*, *62*(2), 629–668. https://doi.org/10.1111/j.1540-6261.2007.01219.x

Wurgler, J. (2000). Financial markets and the allocation of capital. *Journal of Financial Economics*, *58*(1-2), 187–214. https://doi.org/10.1016/S0304-405X(00)00070-2

I first provide the derivation for the direct solution to the baseline problem 1.
The maximization problem can be rewritten as follows:

$$\max_{\{x_{11}^C, x_{11}^D, x_{12}^C, x_{12}^D\}} \quad \frac{1}{(1-\frac{1}{\sigma})L}\{\pi_1 n_1 (d_1^C x_{11}^C)^{1-\frac{1}{\sigma}} + \pi_2 n_2 (d_2^C x_{12}^C)^{1-\frac{1}{\sigma}}$$
$$+ (1-\pi_1) n_1 (d_1^D \theta_1 x_{11}^D)^{1-\frac{1}{\sigma}} + (1-\pi_2) n_2 (d_2^D \theta_1 x_{12}^D)^{1-\frac{1}{\sigma}}\}$$
$$\text{s.t.} \quad p_1[\pi_1 n_1 x_{11}^C + (1-\pi_1) n_1 x_{11}^D] + p_2\tau[\pi_2 n_2 x_{12}^C + (1-\pi_2) n_2 x_{12}^D] \leq n_1 y_1 (1-s_1)$$

Denote the Lagrange multiplier for the budget constraint with λ_1. The FOCs with respect to x_{11}^C, x_{12}^C, x_{11}^D and x_{12}^D are given by:

$$[x_{11}^C]: \quad \frac{\pi_1 n_1 (d_1^C)^{1-1/\sigma} {x_{11}^C}^{-1/\sigma}}{L} = \lambda_1 p_1 \pi_1 n_1$$
$$[x_{12}^C]: \quad \frac{\pi_2 n_2 (d_2^C)^{1-1/\sigma} {x_{12}^C}^{-1/\sigma}}{L} = \lambda_1 p_2 \tau \pi_2 n_2$$
$$[x_{11}^D]: \quad \frac{(1-\pi_1) n_1 (d_1^D \theta_1)^{1-1/\sigma} {x_{11}^D}^{-1/\sigma}}{L} = \lambda_1 p_1 (1-\pi_1) n_1$$
$$[x_{12}^D]: \quad \frac{(1-\pi_2) n_2 (d_2^D \theta_1)^{1-1/\sigma} {x_{12}^D}^{-1/\sigma}}{L} = \lambda_1 p_2 \tau (1-\pi_2) n_2$$

The optimal domestic and foreign lending share in a single project of the two types is thus:

$$x_{11}^C = \frac{{d_1^C}^{\sigma-1}}{(L\lambda_1 p_1)^\sigma} \ \ \& \ \ x_{11}^D = \frac{(d_1^D \theta_1)^{\sigma-1}}{(L\lambda_1 p_1)^\sigma} \ \text{ domestically,}$$
$$x_{12}^C = \frac{{d_2^C}^{\sigma-1}}{(L\lambda_1 p_2 \tau)^\sigma} \ \ \& \ \ x_{12}^D = \frac{(d_2^D \theta_1)^{\sigma-1}}{(L\lambda_1 p_2 \tau)^\sigma} \ \text{ abroad.}$$

I aggregate the values of the per-project shares over the total projects to obtain the lending values to domestic-clean ($\mathbf{X}_{11}^C$), domestic-dirty ($\mathbf{X}_{11}^D$), foreign-clean ($\mathbf{X}_{12}^C$), and foreign-dirty ($\mathbf{X}_{12}^D$) projects:

$$\begin{aligned}
\mathbf{X}_{11}^C &= p_1 \pi_1 n_1 x_{11}^C = p_1 \pi_1 n_1 \frac{{d_1^C}^{\sigma-1}}{(L\lambda_1 p_1)^\sigma} \\
\mathbf{X}_{11}^D &= p_1 (1-\pi_1) n_1 x_{11}^D = p_1 (1-\pi_1) n_1 \frac{(d_1^D \theta_1)^{\sigma-1}}{(L\lambda_1 p_1)^\sigma} \\
\mathbf{X}_{12}^C &= p_2 \tau \pi_2 n_2 x_{12}^C = p_2 \tau \pi_2 n_2 \frac{{d_2^C}^{\sigma-1}}{(L\lambda_1 p_2 \tau)^\sigma} \\
\mathbf{X}_{12}^D &= p_2 \tau (1-\pi_2) n_2 x_{12}^D = p_2 \tau (1-\pi_2) n_2 \frac{(d_2^D \theta_1)^{\sigma-1}}{(L\lambda_1 p_2 \tau)^\sigma}
\end{aligned} \tag{A1}$$

Denote the expected net returns: $R_1^C = \frac{d_1^C}{Lp_1}$, $R_2^C = \frac{d_2^C}{Lp_2}$, $R_1^D = \frac{d_1^D}{Lp_1}$ and $R_2^D = \frac{d_2^D}{Lp_2}$. The budget constraint must bind, yielding:

$$\mathbf{X}_{11}^C + \mathbf{X}_{11}^D + \mathbf{X}_{12}^C + \mathbf{X}_{12}^D = (1-s_1) n_1 y_1$$
$$= \frac{\pi_1 n_1 (R_1^C)^{\sigma-1} + (1-\pi_1) n_1 (R_1^D \theta_1)^{\sigma-1} + \pi_2 n_2 (R_2^C/\tau)^{\sigma-1} + (1-\pi_2) n_2 (R_2^D \theta_1/\tau)^{\sigma-1}}{L\lambda_1^\sigma}$$

Denote the total number of clean projects as M_C and the total number of dirty projects as M_D. Define the project-type-specific return indexes, $\bar{R}_C \equiv \frac{\pi_1 n_1}{M_C}(R_1^C)^{\sigma-1} + \frac{\pi_2 n_2}{M_C}(R_2^C)^{\sigma-1}$ and $\bar{R}_D \equiv \frac{(1-\pi_1)n_1}{M_D}(R_1^D)^{\sigma-1} + \frac{(1-\pi_2)n_2}{M_D}(R_2^D)^{\sigma-1}$, and additionally a foreign return index $\bar{R}_{12} = \frac{\pi_2 n_2}{n_2}(R_2^C)^{\sigma-1} + \frac{(1-\pi_2)n_2}{n_2}(R_2^D\theta_1)^{\sigma-1}$. The Lagrangian multiplier λ_1 can be solved from:

$$\lambda_1^\sigma = \frac{\frac{M_C}{L}\bar{R}_C + \frac{M_D}{L}\theta_1^{\sigma-1}\bar{R}_D - (1-\tau^{1-\sigma})\frac{n_2}{L}\bar{R}_{12}}{(1-s_1)n_1 y_1} \tag{A2}$$

The full portfolio return of Country 1 can be rewritten using the return indexes, i.e., $\mathbf{R_1} = \frac{M_C}{L}\bar{R}_C + \frac{M_D}{L}\theta_1^{\sigma-1}\bar{R}_D - (1-\tau^{1-\sigma})\frac{n_2}{L}\bar{R}_{12}$. Country 1's aggregate lending to domestic-clean ($\mathbf{X}_{11}^C$), domestic-dirty ($\mathbf{X}_{11}^D$), foreign-clean ($\mathbf{X}_{12}^C$), and foreign-dirty ($\mathbf{X}_{12}^D$) projects can be obtained by replacing λ_1 from Equation system A1 with Equation A2:

$$\mathbf{X}_{11}^C = \frac{\pi_1 n_1}{L}\,(1-s_1)n_1 y_1\,\frac{(R_1^C)^{\sigma-1}}{\mathbf{R_1}} \quad \& \quad \mathbf{X}_{11}^D = \frac{(1-\pi_1)n_1}{L}\,(1-s_1)n_1 y_1\,\frac{(R_1^D\theta_1)^{\sigma-1}}{\mathbf{R_1}},$$
$$\mathbf{X}_{12}^C = \frac{\pi_2 n_2}{L}\,(1-s_1)n_1 y_1\,\frac{(R_2^C/\tau)^{\sigma-1}}{\mathbf{R_1}} \quad \& \quad \mathbf{X}_{12}^D = \frac{(1-\pi_2)n_2}{L}\,(1-s_1)n_1 y_1\,\frac{(R_2^D\theta_1/\tau)^{\sigma-1}}{\mathbf{R_1}}.$$

Bank 2 faces a symmetric problem, and thus its lending flows can be obtained likewise.

The corresponding lending weights (in the total portfolios) are given by:

$$\begin{aligned} W_{11}^C &= \frac{\pi_1 n_1}{L}\frac{(R_1^C)^{\sigma-1}}{\mathbf{R_1}} \quad \& \quad W_{11}^D = \frac{(1-\pi_1)n_1}{L}\frac{(R_1^D\theta_1)^{\sigma-1}}{\mathbf{R_1}} \\ W_{12}^C &= \frac{\pi_2 n_2}{L}\frac{(R_2^C/\tau)^{\sigma-1}}{\mathbf{R_1}} \quad \& \quad W_{12}^D = \frac{(1-\pi_2)n_2}{L}\frac{(R_2^D\theta_1/\tau)^{\sigma-1}}{\mathbf{R_1}} \end{aligned} \tag{A3}$$

The total clean and dirty lending values by Country 1 are given by:

$$\mathbf{X}_1^C = \mathbf{X}_{11}^C + \mathbf{X}_{12}^C = \frac{M_C}{L}\frac{(1-s_1)n_1 y_1}{\mathbf{R_1}}[\bar{R}_C - \frac{\pi_2 n_2}{M_C}(1-\tau^{1-\sigma})(R_2^C)^{\sigma-1}],$$
$$\mathbf{X}_1^D = \mathbf{X}_{11}^D + \mathbf{X}_{12}^D = \frac{M_D}{L}\frac{(1-s_1)n_1 y_1}{\mathbf{R_1}}\theta_1^{\sigma-1}[\bar{R}_D - \frac{(1-\pi_2)n_2}{M_D}(1-\tau^{1-\sigma})(R_2^D)^{\sigma-1}].$$

The total green and brown lending weights of Country 1 are:

$$\begin{aligned} W_1^C &= \frac{\mathbf{X}_C}{(1-s_1)n_1 y_1} = \frac{M_C}{L}\frac{\bar{R}_C - \frac{\pi_2 n_2}{M_C}(1-\tau^{1-\sigma})(R_2^C)^{\sigma-1}}{\mathbf{R_1}}, \\ W_1^D &= \frac{\mathbf{X}_D}{(1-s_1)n_1 y_1} = \frac{M_D}{L}\theta_1^{\sigma-1}\frac{\bar{R}_D - \frac{(1-\pi_2)n_2}{M_D}(1-\tau^{1-\sigma})(R_2^D)^{\sigma-1}}{\mathbf{R_1}}. \end{aligned} \tag{A4}$$

The problem faced by Bank 2 is symmetric. Country 2's lending flows are

$$\mathbf{X}_{21}^C = \frac{\pi_1 n_1}{L}\,(1-s_2)n_2 y_2\,\frac{(R_1^C/\tau)^{\sigma-1}}{\mathbf{R_2}}, \quad \& \quad \mathbf{X}_{21}^D = \frac{(1-\pi_1)n_1}{L}\,(1-s_2)n_2 y_2\,\frac{(R_1^D\theta_2/\tau)^{\sigma-1}}{\mathbf{R_2}},$$
$$\mathbf{X}_{22}^C = \frac{\pi_2 n_2}{L}\,(1-s_2)n_2 y_2\,\frac{(R_2^C)^{\sigma-1}}{\mathbf{R_2}}, \quad \& \quad \mathbf{X}_{22}^D = \frac{(1-\pi_2)n_2}{L}\,(1-s_2)n_2 y_2\,\frac{(R_2^D\theta_2)^{\sigma-1}}{\mathbf{R_2}}.$$

where $\mathbf{R_2} = \frac{\pi_2 n_2}{L}(R_2^C)^{\sigma-1} + \frac{\pi_1 n_1}{L}(\frac{R_1^C}{\tau})^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(\theta_2 R_2^D)^{\sigma-1} + \frac{(1-\pi_1)n_1}{L}(\frac{\theta_2 R_1^D}{\tau})^{\sigma-1}$.

I provide proof for propositions and lemmas below.

Proof (Lemma 1). *Consider Country 1. Its domestic carbon sensitivity of lending is given by*

$$\log \mathbf{X}_{11}^C - \log \mathbf{X}_{11}^D = \log\left(\frac{\pi_1 n_1}{L}\ (1-s_1)n_1 y_1\ \frac{(R_1^C)^{\sigma-1}}{\mathbf{R_1}}\right) - \log\left(\frac{(1-\pi_1)n_1}{L}\ (1-s_1)n_1 y_1\ \frac{(R_1^D\theta_1)^{\sigma-1}}{\mathbf{R_1}}\right)$$
$$= \log(\frac{\pi_1}{1-\pi_1}) + (\sigma-1)\log\frac{R_1^C}{R_1^D} - (\sigma-1)log\theta_1$$

Its foreign carbon sensitivity of lending is given by

$$\log \mathbf{X}_{12}^C - \log \mathbf{X}_{12}^D = \log\left(\frac{\pi_2 n_2}{L}\ (1-s_1)n_1 y_1\ \frac{(R_2^C/\tau)^{\sigma-1}}{\mathbf{R_1}}\right) - \log\left(\frac{(1-\pi_2)n_2}{L}\ (1-s_1)n_1 y_1\ \frac{(R_2^D\theta_1/\tau)^{\sigma-1}}{\mathbf{R_1}}\right)$$
$$= \log(\frac{\pi_2}{1-\pi_2}) + (\sigma-1)\log\frac{R_2^C}{R_2^D} - (\sigma-1)log\theta_1$$

The same result holds when comparing weights instead of total lending values. The right-hand sides of the equations remain unchanged.

$$\log W_{11}^C - \log W_{11}^D = \log\left(\frac{\pi_1 n_1}{L}\frac{(R_1^C)^{\sigma-1}}{\mathbf{R_1}}\right) - \log\left(\frac{(1-\pi_1)n_1}{L}\frac{(R_1^D\theta_1)^{\sigma-1}}{\mathbf{R_1}}\right)$$
$$= \log(\frac{\pi_1}{1-\pi_1}) + (\sigma-1)\log\frac{R_1^C}{R_1^D} - (\sigma-1)log\theta_1;$$
$$\log W_{12}^C - \log W_{12}^D = \log\left(\frac{\pi_2 n_2}{L}\frac{(R_2^C/\tau)^{\sigma-1}}{\mathbf{R_1}}\right) - \log\left(\frac{(1-\pi_2)n_2}{L}\frac{(R_2^D\theta_1/\tau)^{\sigma-1}}{\mathbf{R_1}}\right)$$
$$= \log(\frac{\pi_2}{1-\pi_2}) + (\sigma-1)\log\frac{R_2^C}{R_2^D} - (\sigma-1)log\theta_1.$$

Furthermore, a country's full portfolio carbon sensitivity of lending can also be written in a similar form:

$$log(\frac{\mathbf{X}_i^C}{\mathbf{X}_i^D}) = \log(\frac{M_C}{M_D}) + (\sigma-1)(\log\tilde{R}_i^C - \log\tilde{R}_i^D) - (\sigma-1)\log\theta_i,$$

where $\tilde{R}_i^C = \frac{\pi_1 n_1}{M_C}(R_1^C)^{\sigma-1} + \frac{\pi_2 n_2}{M_C}(R_2^C/\tau)^{\sigma-1}$ *and* $\tilde{R}_i^D = \frac{(1-\pi_1)n_1}{M_D}(R_1^D)^{\sigma-1} + \frac{(1-\pi_2)n_2}{M_D}(R_2^D/\tau)^{\sigma-1}$. *This last result holds when comparing weights* W_i^C *to* W_i^D.

Proof (Proposition 1)**.** *Consider a change in brown lending resistance of Country 1, for example. Given that* θ_1 *is independent from* π_1, R_1^C *and* R_D^H*, an decrease in* θ_1 *changes the lending flows* $\mathbf{X}_{12}^C$ *and* $\mathbf{X}_{22}^C$ *through* $\mathbf{R}_1$ *indirectly, and* $\mathbf{X}_{12}^D$ *and* $\mathbf{X}_{22}^D$ *through both* $\mathbf{R}_1$ *indirectly and* θ_1 *directly. I first show how* $\mathbf{R}_1$ *changes with* θ_1*:*

$$\frac{\partial \mathbf{R}_1}{\partial \theta} = (\sigma-1)\frac{(1-\pi_1)n_1}{L}(R_1^D)^{\sigma-1}\theta_1^{\sigma-2} > 0.$$

For each lending flow, I derive the first order derivative with respect to θ_1*:*

$$\frac{\partial \mathbf{X}_{11}^C}{\partial \theta_1} = -\frac{\mathbf{X}_{11}^C}{\mathbf{R}_1}\frac{\partial \mathbf{R}_1}{\partial \theta_1} < 0, \qquad \frac{\partial \mathbf{X}_{12}^C}{\partial \theta} = -\frac{\mathbf{X}_{12}^C}{\mathbf{R}_1}\frac{\partial \mathbf{R}_1}{\partial \theta} < 0,$$

$$\frac{\partial \mathbf{X}_{11}^D}{\partial \theta_1} = \underbrace{\left(\frac{(1-\pi_1)n_1}{L}(1-s_1)n_1 y_1 (R_1^D)^{\sigma-1}\right)(\sigma-1)\theta_1^{\sigma-2}R_1^{-1}}_{>0}\left[1 - \underbrace{\frac{\frac{(1-\pi_1)n_1}{L}(\theta_1 R_1^D)^{\sigma-1}}{\mathbf{R}_1}}_{\in(0,1)}\right] > 0,$$

$$\frac{\partial \mathbf{X}_{12}^D}{\partial \theta_1} = \underbrace{\left(\frac{(1-\pi_2)n_2}{L}(1-s_1)n_1 y_1 (R_2^D/\tau)^{\sigma-1}\right)(\sigma-1)\theta_1^{\sigma-2}R_1^{-1}}_{>0}\left[1 - \underbrace{\frac{\frac{(1-\pi_1)n_1}{L}(\theta_1 R_1^D)^{\sigma-1}}{\mathbf{R}_1}}_{\in(0,1)}\right] > 0.$$

Corresponding changes in the aggregate lending flows can be obtained subsequently:

$$\frac{\partial \mathbf{X}_1^C}{\partial \theta_1} = \frac{\partial \mathbf{X}_{11}^C}{\partial \theta_1} + \frac{\partial \mathbf{X}_{11}^C}{\partial \theta_1} < 0$$

$$\frac{\partial \mathbf{X}_1^D}{\partial \theta_1} = \frac{\partial \mathbf{X}_{11}^D}{\partial \theta_1} + \frac{\partial \mathbf{X}_{11}^D}{\partial \theta_1} > 0$$

The domestic carbon sensitivity of lending $\log(\frac{\mathbf{X}_{11}^C}{\mathbf{X}_{11}^D}) = \log(\frac{\pi_1}{1-\pi_1}) + (\sigma-1)(\log R_1^C - \log R_1^D) - (\sigma-1)log\theta_1$ *increases as* θ_1 *(or* $\log\theta_1$*) decreases, because*

$$\frac{\partial(\log \mathbf{X}_{11}^C - \log \mathbf{X}_{11}^D)}{\partial \log \theta_1} = 1-\sigma < 0, \quad \textit{given } \sigma > 1.$$

$$\textit{and} \quad \frac{\partial(\log \mathbf{X}_{11}^C - \log \mathbf{X}_{11}^D)}{\partial \theta_1} = \frac{1-\sigma}{\theta_1} < 0, \quad \textit{given } \sigma > 1 \textit{ and } 0 < \theta_1 \le 1.$$

In the same way, the foreign carbon sensitivity of lending $\log(\frac{\mathbf{X}_{12}^C}{\mathbf{X}_{12}^D}) = log(\frac{\pi_2}{1-\pi_2}) + (\sigma-1)(logR_2^C - logR_2^D) - (\sigma-1)log\theta_1$ *also increases as* θ_1 *(or* $\log\theta_1$*) decreases.*

A change in θ_1 *does not affect other country's lending flows when* θ_1 *and* θ_2 *are independent. Foreign lending flows are determined by its own brown lending resistance* θ_2.

Note that an increase of θ means a decrease in brown lending resistance. When the pro-environmental preference or supervision strengthens, θ decreases.

Proof (Lemma 2)**.** *The result follows from the previous proof. Consider Country 1:*

$$\frac{\partial(\log \mathbf{X}_{11}^C - \log \mathbf{X}_{11}^D)}{\partial \theta_1} = \frac{\partial(\log \mathbf{X}_{12}^C - \log \mathbf{X}_{12}^D)}{\partial \theta_1} = \frac{1-\sigma}{\theta_1} < 0.$$

Proof (Lemma 3)**.** *Consider Country 1. The difference in the levels of carbon sensitivity of lending on two markets is given by:*

$$\log(\frac{\mathbf{X}_{11}^C}{\mathbf{X}_{11}^D}) - \log(\frac{\mathbf{X}_{12}^C}{\mathbf{X}_{12}^D}) = \log\frac{\pi_1/(1-\pi_1)}{\pi_2/(1-\pi_2)} - \log\frac{R_1^C/R_1^D}{R_2^C/R_2^D}.$$

Next, I discuss two different climate policies, one reducing the return of domestic dirty projects and the other increasing the domestic share of clean projects.

Proof (Proposition 2)**.** *Consider a domestic policy change of Country 1, for example. A decrease in* R_1^D *lowers the aggregate return index* $\mathbf{R}_1$ *of the country because:*

$$\frac{\partial \mathbf{R}_1}{\partial R_1^D} = \frac{(1-\pi_1)n_1}{L}\theta_1^{\sigma-1}(\sigma-1)(R_1^D)^{\sigma-2} > 0.$$

A change in R_1^D *affects* $\mathbf{X}_{11}^C$ *and* $\mathbf{X}_{12}^C$ *and* $\mathbf{X}_{12}^D$ *through* $\mathbf{R}_1$*, and so:*

$$\frac{\partial \mathbf{X}_{11}^C}{\partial R_1^D} = -\frac{\mathbf{X}_{11}^C}{\mathbf{R}_1}\frac{\partial \mathbf{R}_1}{\partial R_1^D} < 0, \qquad \frac{\partial \mathbf{X}_{12}^C}{\partial R_1^D} = -\frac{\mathbf{X}_{12}^C}{\mathbf{R}_1}\frac{\partial \mathbf{R}_1}{\partial R_1^D} < 0, \qquad \frac{\partial \mathbf{X}_{12}^D}{\partial R_1^D} = -\frac{\mathbf{X}_{12}^C}{\mathbf{R}_1}\frac{\partial \mathbf{R}_1}{\partial R_1^D} < 0.$$

A change in R_1^D *affects* $\mathbf{X}_{11}^D$ *through both* $\mathbf{R}_1$ *and* R_1^D*:*

$$\frac{\partial \mathbf{X}_{11}^D}{\partial R_1^D} = \underbrace{\left(\frac{(1-\pi_1)n_1}{L}(1-s_1)n_1y_1(\theta_1)^{\sigma-1}\right)(\sigma-1)(R_1^D)^{\sigma-2}R_1^{-1}}_{>0}\left[1 - \underbrace{\frac{\frac{(1-\pi_1)n_1}{L}(\theta_1 R_1^D)^{\sigma-1}}{\mathbf{R}_1}}_{\in(0,1)}\right] > 0$$

The corresponding change in the aggregate clean lending flow can be obtained directly

$$\frac{\partial \mathbf{X}_1^C}{\partial R_1^D} = \frac{\partial \mathbf{X}_{11}^C}{\partial R_1^D} + \frac{\partial \mathbf{X}_{11}^C}{\partial R_1^D} < 0.$$

The corresponding change in the aggregate dirty lending flow can be obtained by computing the aggregate changes through $\mathbf{X}_{11}^D$ and $\mathbf{X}_{12}^D$. But there is an easier way to obtain it, which is by using the binding budget constraint:

$$\frac{\partial \mathbf{X}_1^D}{\partial R_1^D} = \frac{\partial[(1-s_1)n_1 y_1 - \mathbf{X}_1^C]}{\partial R_1^D} = -\frac{\partial \mathbf{X}_1^C}{\partial R_1^D} > 0.$$

Moreover, the domestic carbon sensitivity of lending $\log(\frac{\mathbf{X}_{11}^C}{\mathbf{X}_{11}^D})$ increases as R_1^D decreases, because

$$\frac{\partial(\log \mathbf{X}_{11}^C - \log \mathbf{X}_{11}^D)}{\partial R_1^D} = \frac{1-\sigma}{R_1^D} < 0, \quad \text{given } \sigma > 1 \text{ and } R_1^D > 0.$$

The foreign carbon sensitivity of lending does not change as it does not depend on R_1^D.

Next, I consider the changes in Country 2's lending flows. A change in R_1^D also affects the lending flows $\mathbf{X}_{21}^C$, $\mathbf{X}_{22}^C$ and $\mathbf{X}_{22}^D$ by Country 2 through Country 2's aggregate return index $\mathbf{R}_2$:

$$\frac{\partial \mathbf{R}_2}{\partial R_1^D} = \frac{(1-\pi_1)n_1}{L}(\frac{\theta_2}{\tau})^{\sigma-1}(\sigma-1)(R_1^D)^{\sigma-2} > 0.$$

Similarly as in the case of Country 1, $\frac{\partial \mathbf{X}_{21}^C}{\partial R_1^D} = \frac{\partial \mathbf{X}_{21}^C}{\partial \mathbf{R}_2}\frac{\partial \mathbf{R}_2}{\partial R_1^D} < 0$, $\frac{\partial \mathbf{X}_{22}^C}{\partial R_1^D} = \frac{\partial \mathbf{X}_{22}^C}{\partial \mathbf{R}_2}\frac{\partial \mathbf{R}_2}{\partial R_1^D} < 0$, *and* $\frac{\partial \mathbf{X}_{22}^D}{\partial R_1^D} = \frac{\partial \mathbf{X}_{22}^D}{\partial \mathbf{R}_2}\frac{\partial \mathbf{R}_2}{\partial R_1^D} < 0$. *A change in R_1^D affects $\mathbf{X}_{21}^D$ through $\mathbf{R}_2$ as well as R_1^D:*

$$\frac{\partial \mathbf{X}_{21}^D}{\partial R_1^D} = \underbrace{\left(\frac{(1-\pi_1)n_1}{L}(1-s_2)n_2 y_2(\theta_2/\tau)^{\sigma-1}\right)(\sigma-1)\frac{(R_1^D)^{\sigma-2}}{\mathbf{R_2}}}_{>0}[1-\underbrace{\frac{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_2/\tau)^{\sigma-1}}{\mathbf{R}_2}}_{\in(0,1)}] > 0.$$

The aggregate impact of R_1^D on $\mathbf{X}_2^D$ is equal to

$$\frac{\partial \mathbf{X}_2^D}{\partial R_1^D} = \underbrace{\left(\frac{(1-\pi_1)n_1}{L}(1-s_2)n_2 y_2(\theta_2/\tau)^{\sigma-1}\right)(\sigma-1)\frac{(R_1^D)^{\sigma-2}}{\mathbf{R_2}}}_{>0}\underbrace{[1-\frac{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_2/\tau)^{\sigma-1}}{\mathbf{R}_2} - \frac{\frac{(1-\pi_2)n_2}{L}(R_2^D\theta_2)^{\sigma-1}}{\mathbf{R}_2}]}_{>0} > 0.$$

Country 2's carbon sensitivity of lending can change accordingly:

$$\frac{\partial(\log X_{21}^C - \log X_{21}^D)}{\partial R_1^D} = (1-\sigma)\frac{1}{R_1^D} < 0, \quad \& \quad \frac{\partial(\log X_{22}^C - \log X_{22}^D)}{\partial R_1^D} = 0.$$

That is, Country 2's domestic carbon sensitivity of lending is unaffected while its foreign carbon sensitivity increases as R_1^D decreases.

Proof (Proposition 3)**.** *Consider a domestic policy change of Country 1, for example. I first consider the lending changes for Country 1. How a decrease (increase) in $1-\pi_1$ (π_1) changes the aggregate domestic return index depends on the relationship between the clean and dirty returns:*

$$\frac{\partial \mathbf{R}_1}{\partial \pi_1} = \frac{n_1}{L}[(R_1^C)^{\sigma-1} - (\theta_1 R_1^D)^{\sigma-1}] \quad \begin{cases} > 0 & \text{if } R_1^C > \theta_1 R_1^D, \\ < 0 & \text{if } R_1^C < \theta_1 R_1^D. \end{cases}$$

Depending on the sign of $(R_1^C)^{\sigma-1} - (\theta_1 R_1^D)^{\sigma-1}$, the lending flows can have different changes.

- *When carbon premium persists after brown lending resistance ($R_1^C < \theta_1 R_1^D$), the aggregate return index decreases as a domestic climate policy reduces the loan demand by dirty projects. Similarly as in the previous proof, a decrease in the aggregate return index leads to higher foreign clean lending ($\frac{\partial \mathbf{X}_{12}^C}{\partial \pi_1} > 0$) and higher foreign dirty lending ($\frac{\partial \mathbf{X}_{12}^D}{\partial \pi_1} > 0$). This change in the loan demand structure affects domestic lending flows through the loan demand directly as well as the aggregate return indirectly:*

$$\frac{\partial \mathbf{X}_{11}^C}{\partial \pi_1} = \frac{n_1}{L}(1-s_1)n_1y_1(R_1^C)^{\sigma-1}\mathbf{R}_1^{-2}\left(\frac{n_2\pi_2}{L}(\frac{R_2^C}{\tau})^{\sigma-1} + \frac{(\theta_1R_1^D)^{\sigma-1}}{L} + \frac{(1-\pi_2)n_2}{L}(\frac{\theta_1R_2^D}{\tau})^{\sigma-1}\right) > 0;$$

$$\frac{\partial \mathbf{X}_{11}^D}{\partial \pi_1} = \frac{n_1}{L}(1-s_1)n_1y_1(\theta_1R_1^D)^{\sigma-1}(-\mathbf{R}_1^{-1})\left(\frac{(R_1^C)^{\sigma-1} + \frac{\pi_2n_2}{L}(\frac{R_2^C}{\tau})^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(\frac{\theta_1R_2^D}{\tau})^{\sigma-1}}{\mathbf{R}_1}\right) < 0.$$

The total lending to clean projects $\mathbf{X}_1^C$ increases ($\frac{\partial \mathbf{X}_1^C}{\partial \pi_1} > 0$). The change in the total lending to dirty projects $\mathbf{X}_1^D$ can be positive or negative depending on the relative strengths of two opposing effects:

$$\frac{\partial \mathbf{X}_1^D}{\partial \pi_1} = \frac{(1-s_1)n_1^2y_1}{L(\mathbf{R}_1)^2}\Bigg\{\underbrace{-(R_1^D\theta_1)^{\sigma-1}\mathbf{R}_1}_{\text{direct effect through loan demand reduction: negative}}$$

$$+\underbrace{\left[\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_1)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(\frac{R_2^D\theta_1}{\tau})^{\sigma-1}\right][(\theta_1R_1^D)^{\sigma-1} - (R_1^C)^{\sigma-1}]}_{\text{indirect effect due to aggregate return decrease: positive}}\Bigg\}$$

$$\begin{cases} > 0 & \text{if} \quad \theta_1R_1^D - R_1^C > \frac{(R_1^D\theta_1)^{\sigma-1}\mathbf{R}_1}{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_1)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(\frac{R_2^D\theta_1}{\tau})^{\sigma-1}} \\ < 0 & \text{if} \quad \theta_1R_1^D - R_1^C < \frac{(R_1^D\theta_1)^{\sigma-1}\mathbf{R}_1}{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_1)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(\frac{R_2^D\theta_1}{\tau})^{\sigma-1}} \end{cases}$$

Lastly, only the domestic carbon sensitivity of lending changes:

$$\frac{\partial(\log \mathbf{X}_{11}^C - \log \mathbf{X}_{11}^D)}{\partial \pi_1} = \frac{1}{\pi_1} + \frac{1}{1-\pi_1} > 0.$$

- *When brown lending resistance creates a green premium ($R_1^C > \theta_1R_1^D$), the aggregate return index increases as a domestic policy reduces the loan demand by dirty projects. A higher $\mathbf{R}_1$ leads to lower foreign lending flows. However, the corresponding changes in the domestic lending flows are the same as in the previous case. That is, an increase in π_1 increases $\mathbf{X}_{11}^C$ and decreases $\mathbf{X}_{11}^D$. As a result, the total clean lending increases. Given $\theta_1R_1^D - R_1^C < 0$, the total dirty lending decreases. Again, only the domestic carbon sensitivity of lending increases.*

I next consider the corresponding changes for Country 2. Similarly,

$$\frac{\partial \mathbf{R}_2}{\partial \pi_1} = \frac{n_1}{L\tau^{\sigma-1}}[(R_1^C)^{\sigma-1} - (\theta_2R_1^D)^{\sigma-1}] \quad \begin{cases} > 0 & \text{if } R_1^C > \theta_2R_1^D, \\ < 0 & \text{if } R_1^C < \theta_2R_1^D. \end{cases}$$

Regardless of the sign of $(R_1^C)^{\sigma-1} - (\theta_2R_1^D)^{\sigma-1}$, the foreign clean lending of Country 2 increases while the foreign dirty lending decreases:

$$\frac{\partial \mathbf{X}_{21}^C}{\partial \pi_1} = \frac{(R_1^C/\tau)^{\sigma-1}n_1}{L(\mathbf{R}_2)^2}(1-s_2)n_2y_2\{\mathbf{R}_2 - \frac{n_1\pi_1}{L\tau^{\sigma-1}}[(R_1^C)^{\sigma-1} - (\theta_2R_1^D)^{\sigma-1}]\} > 0;$$

$$\frac{\partial \mathbf{X}_{21}^D}{\partial \pi_1} = -\frac{(\theta_2R_1^D/\tau)^{\sigma-1}n_1}{L(\mathbf{R}_2)^2}(1-s_2)n_2y_2\{\mathbf{R}_2 + \frac{(1-\pi_1)n_1}{L\tau^{\sigma-1}}[(R_1^C)^{\sigma-1} - (\theta_2R_1^D)^{\sigma-1}]\} < 0.$$

The corresponding changes in other lending flows depend on the sign of $(R_1^C)^{\sigma-1} - (\theta_2R_1^D)^{\sigma-1}$.

- *When $R_1^C < \theta_2R_1^D$, $\mathbf{R}_2$ decreases. As a result, $\mathbf{X}_{22}^C$ and $\mathbf{X}_{22}^D$ increases. The total clean lending flow of Country 2 $\mathbf{X}_2^C$ increases. The total dirty lending flow of Country 2 $\mathbf{X}_2^D$ can again increase or decrease depending on the size of $\theta_2R_1^D - R_1^C$:*

$$\frac{\partial \mathbf{X}_2^D}{\partial \pi_1} = \frac{(1-s_2)n_2y_2n_1}{L\mathbf{R}_2^2\tau^{\sigma-1}} \Bigg\{ \underbrace{-(R_1^D\theta_2)^{\sigma-1}\mathbf{R}_2}_{\text{direct effect through loan demand reduction: negative}}$$

$$+ \underbrace{\left[\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_2/\tau)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(R_2^D\theta_2)^{\sigma-1}\right][(\theta_1R_1^D)^{\sigma-1} - (R_1^C)^{\sigma-1}]}_{\text{indirect effect due to aggregate return decrease: positive}} \Bigg\}$$

$$\begin{cases} > 0 & \text{if} \quad \theta_1R_1^D - R_1^C > \frac{(R_1^D\theta_2)^{\sigma-1}\mathbf{R}_2}{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_2/\tau)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(R_2^D\theta_2)^{\sigma-1}} \\ < 0 & \text{if} \quad \theta_1R_1^D - R_1^C < \frac{(R_1^D\theta_2)^{\sigma-1}\mathbf{R}_2}{\frac{(1-\pi_1)n_1}{L}(R_1^D\theta_2/\tau)^{\sigma-1} + \frac{(1-\pi_2)n_2}{L}(R_2^D\theta_2)^{\sigma-1}}. \end{cases}$$

Lastly, only the foreign carbon sensitivity of lending increases:

$$\frac{\partial(\log \mathbf{X}_{21}^C - \log \mathbf{X}_{21}^D)}{\partial \pi_1} = \frac{1}{\pi_1} + \frac{1}{1-\pi_1} > 0.$$

- *When $R_1^C > \theta_2 R_1^D$, $\mathbf{R}_2$ increases. As a result, $\mathbf{X}_{22}^C$ and $\mathbf{X}_{22}^D$ decreases. The total clean lending flow of Country 2 $\mathbf{X}_2^C$ increases. The total dirty lending flow of Country 2 $\mathbf{X}_2^D$ decreases. Lastly, the foreign carbon sensitivity of lending increases.*

ECB'S GREEN EXPECTATIONS

B1. Final guide on climate-related and environmental risks for banks

While the central banks and financial regulators in many countries have started tackling climate risks in their financial systems, the European Union has always been recognized as the green finance leader. Figure B1 provides a chronological overview of the publications on climate change for banking supervision at the European Central Bank (ECB).[39] Since 2019, the ECB has started pinning climate risk management high on its policy-making agenda for bank supervision and incorporating climate-related risk supervision into its mandate.

On November 27, 2020, the ECB published the final guide on climate-related and environmental risks (hereafter *C&E risks*) for banks, formalizing its EU-wide supervisory expectations for banks to inspect and manage their climate-related risks internally. The publication of this guide marks an important step in the ECB's green banking progress. Although the guide does not impose any binding ratio requirements, it brings about non-negligible supervisory pressures.

To summarize, the guide communicates to the European banks three key supervisory green expectations. First, the banks are expected to understand the impact of C&E risks and integrate these risk considerations into their business strategy, internal management, risk appetite framework, and organizational structure. Second, banks are expected to report additional data regarding their exposures to C&E risks to supervisors. Third, banks are expected to adjust their risk assessment and credit-granting processes and monitor the C&E risk exposure and its impact to ensure capital adequacy and business continuity.

During the following years, the ECB continues to maintain a strong presence both within and outside the EU through policy communication and general mobilization. The use of words in the ECB's publications also directly displays the ECB's tightening attitude toward the non-alignment of banks' practices with green expectations. Moreover, the ECB shows its decisive stance by escalating the threat of punitive consequences towards banks that do not comply with the green expectations. According to Frank Elderson's

[39]The ECB collects the press releases, speeches, interviews, and other publications concerning climate change in bank supervision, available on https://www.bankingsupervision.europa.eu/home/search/html/climate_change.en.html.

	Banking Supervision and Climate Change	Keywords of the year
2016	(DNB started incorporating climate risks into bank supervision)	
Nov 4	*Paris Agreement entered into force*	
2017	Network for Greening the Financial System was created (chaired by Frank Elderson)	
2018	Frank Elderson joined the supervisory board	
2019		"encourage (banks / central banks and supervisors)", "a greater focus on sustainable finance may emerge naturally", "absence of regulation", "proposals", "understanding", "define and measure climate risks", "early stages"
May 15	*Start of ECB Publications on Climate Change — Interview with Frank Elderson*	
2020		"under the current prudential framework", "(ECB) committed", "raise industry awareness ", "a basis for the supervisory dialogue", "expect (to start)", "applied consistently across the euro area", "identify and assess", "significant challenges", "continue to develop", "concrete steps"
May 20	*Public consultation on ECB's guide on climate-related and environmental risks*	
Nov 27	***ECB published final guide on climate-related and environmental risks for banks***	
2021	Intense speeches (and blog post) by Frank Elderson (Vice-Chair of the Supervisory Board since Feb 24): Apr 29, Jun 3, Jun 16, Sep 23, Oct 19, Oct 20, Nov 3, Nov 4, Nov 22, Dec 10	"compel / push banks", "must", "(Euro area banks need to) drastically improve", "jump (move forcefully / urgently)", "too slow", "(ECB) urges banks to take swifter action", "fall short of expectations", "only partially or not at all aligned", "Paris-compliant transition plan", "significant shortcomings"
Oct 18	*Banks informed about ECB Climate Risk Stress Test*	
2022		"immersive supervisory approach to C&E risks", "only one way forward", "significant gaps remain despite progress", "stricter regulation", "in times of uncertainty", "positive changes / more closely aligned", "learning exercise", "set deadlines", "supervisory consequences", "enforcement action"
Jan 27	*ECB Banking Supervision launches 2022 climate risk stress test*	
Jul 8	*2022 Climate stress test result*	
Oct, Nov 2 Dec 19	*Thematic review on C&E risks, good practices for C&E risk management & for climate stress testing*	
2023		"concrete formal global consensus", "full compliance with all the supervisory expectations for all banks", "closely monitor", "bank-specific deadlines / end of 2024 at the latest", "supervisory escalation to ensure compliance", "must continue improving", "litigation risks", "opportunity"
Apr 21	*Third assessment of the progress European banks have made in disclosing C&E risks*	
2024		
Jan 23	*Assessment of the alignment of the European banking sector*	

FIGURE B1. ROADMAP OF ECB CLIMATE BANKING SUPERVISION

Figure B1 provides a chronological summary of the publications on climate change for banking supervision at the European Central Bank (ECB). I sourced the information from https://www.bankingsupervision.europa.eu/home/search/html/climate_change.en.html.

speech on March 14, 2024, who is a member of the Executive Board of the ECB and vice-chair of the Supervisory Board of the ECB, "these include imposing periodic penalty payments and setting Pillar 2 capital requirements as part of the annual Supervisory Review and Evaluation Process."

B2. Supervisory strata with the Single Supervisory Mechanism

The final guide on climate-related and environmental risks for banks lays the foundation for the general prudential framework covering all supervised institutions under the ECB's supervision. This supervision basis consists of two groups of institutions, namely significant institutions (SIs) and less significant institutions (LSIs), as identified by the Single Supervisory Mechanism (SSM). Given the fact that not all banks operating in the EU are supervised and not only banks can operate in the loan market, the supervisory green expectations are in fact combined with three levels of practical verifiability.[40] Non-compliance with the green expectations has been credibly inspected for SIs since 2021, whereas LSIs are followed by their national competent authorities under the principle of proportionality.

There are certain disparities in the national progress of climate supervision. Some national supervision may have started before the guide was published. For example, De Nederlandsche Bank (DNB) implied in its 2020 annual report that climate risk assessment had been embodied into the supervision of less significant institutions prior to the publication of the ECB's guide on climate-related and environmental risks. On the other hand, other national competent authorities may still be in the process of officially incorporating the ECB's expectations into their national supervision.

All other financial institutions in the European Union received the same signal, but they might interpret the signal in the opposite way as their practices have not yet been supervised.

EMPIRICAL APPENDIX

C1. Additional Tables and Figures

TABLE C1— VARIABLE DEFINITIONS AND SOURCES

Variable	Description	Data Source
Bilateral lending, total	Sector-specific syndicated loan flows in a year from one country to another, including domestic lending.	LPC DealScan.
Bilateral lending, foreign	Sector-specific syndicated loan flows in a year from one country to another, excluding domestic lending.	LPC DealScan.
Sectoral weight (%), total	Value weight of sectoral loans in a country's total lending portfolio in a year.	LPC DealScan.
Sectoral weight (%), domestic	Value weight of sectoral loans in a country's domestic lending portfolio in a year.	LPC DealScan.
Sectoral weight (%), foreign	Value weight of sectoral loans in a country's foreign lending portfolio in a year.	LPC DealScan.
Reported sectoral loans	Total loan amount by a direct lender to each sector in a year, computed on the reported shares.	LPC DealScan.
Reported sectoral loans, domestic	Total domestic loan amount by a direct lender to each sector in a year, computed on the reported shares.	LPC DealScan.
Reported sectoral loans, foreign	Total foreign loan amount by a direct lender to each sector in a year, computed on the reported shares.	LPC DealScan.
Share in a facility (%)	Reported loan share of each direct lender in a loan facility, measured as a percentage.	LPC DealScan.
Total share in a facility (%)	Sum of the reported loan shares of direct lenders with the same parent lender in a loan facility, measured as a percentage.	LPC DealScan.

[40] ECB maintains the list of supervised banks, covering all significant banks and less significant banks.

Table C1 continued from previous page

Variable	Description	Data Source
Agent	Indicator variable for underwriting agents, consisting of "Admin agent", "Agent", "Bookrunner", "Joint arranger", "Lead bank", "Lead manager", "Mandated lead arranger", "Co-agent", "Co-arranger", "Collateral agent", "Coordinating arranger", "Documentation agent", "Managing agent", and "Syndications agent".	LPC DealScan.
Lead arranger	Indicator variable for lead arrangers. I determine the lead arrangers following Chakraborty et al. (2018).	LPC DealScan.
Credit line	Indicator variable if the tranche type is reported to be "364-Day Facility", "Revolver/Line <1 Yr.", or "Revolver/Line >= 1 Yr.".	LPC DealScan.
Term loan	Indicator variable if the tranche type contains "term loan".	LPC DealScan.
Foreign	Indicator variable if the borrower is not from the lender operating country nor the lender parent country.	LPC DealScan.
log GDP per capita	GDP per capita (logarithm) in current USD.	World Bank, United Nations database, and official reports from the national bureaus of statistics.
EI	Sectoral emission intensity on the gross value added.	UK Office for National Statistics, Environmental accounts.
EIR	Emission intensity on revenue, computed as total GHG emissions (Scope 1 + Scope 2) divided by revenues.	GHG emissions: CDP, Refinitiv Workspace. Revenues: Refinitiv.
Bank (Non-bank)	Indicator variable if the entity type is "bank" at the parent lender level.	Orbis.
Weak (Non-weak)	Indicator variable if the Tier 1 ratio of a lender is within the bottom 25 percentiles of the sample.	Orbis.
RCA, based on reported shares	Relative Comparative Advantage measured as the weight of a sector in the given bank's portfolio relative to that in the world portfolio, constructed on the reported shares.	LPC DealScan.
RCA, based on approximated shares	Relative Comparative Advantage measured as the weight of a sector in the given bank's portfolio relative to that in the world portfolio, constructed on the approximated shares.	LPC DealScan.
SI	Significant Institutions identified by the ECB.	ECB banking supervision.
Other SSM-related lender	Indicator variable for financial institutions (or with a parent) operating in the countries within the Single Supervisory Mechanism that are not identified as SI.	LPC DealScan, Orbis.
Post Guide	Indicator variable for years 2015 to 2023, after the publication of the Guide on climate-related and environmental risks.	
Bank deposits (% GDP)	Demand, time and saving deposits in deposit money banks as a share of GDP.	World Bank.
Bank concentration	Assets of three largest commercial banks as a share of total commercial banking assets.	World Bank.
Bank non-performing loans to gross loans	Ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio).	World Bank.
Bank net interest margin	Accounting value of bank's net interest revenue as a share of its average interest-bearing (total earning) assets.	World Bank.
Bank regulatory capital to risk-weighted assets	The capital adequacy of deposit takers. It is a ratio of total regulatory capital to its assets held, weighted according to the risk of those assets.	World Bank.
Financial system deposits (% GDP)	Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP.	World Bank.

Table C1 continued from previous page

Variable	Description	Data Source
Mutual fund asset (% GDP)	Ratio of assets of mutual funds to GDP.	World Bank.
Total value of stocks traded (% GDP)	The value of shares traded as the total number of shares traded, both domestic and foreign, multiplied by their respective matching prices.	World Bank.
Corporate bond issuance (% GDP)	Ratio of new corporate bond issuance volume by private entities in industries other than finance, holding companies and insurance to GDP.	World Bank.
Pension fund assets (% GDP)	Ratio of assets of pension funds to GDP.	World Bank.
Foreign claims (% GDP)	The ratio of consolidated foreign claims to GDP of the banks that are reporting to the BIS. Foreign claims are defined as the sum of cross-border claims plus foreign offices' local claims in all currencies.	World Bank.
Syndicated loan issuance (% GDP)	Ratio of new syndicated borrowing volume by private entities in industries other than finance, holding companies and insurance to GDP.	World Bank.
Heating degree days	Number of degrees that a day's average temperature is below 18.3°C.	World Bank.
Renewable energy share in consumption	Renewable energy consumption is the share of renewable energy in total final energy consumption.	World Bank.
Trade of environmental goods	The proportion of a country's total exports that consist of environmental goods. These goods include products that contribute to environmental protection, resource management, or are specifically modified to be more environmentally friendly, such as clean technology or pollution control devices.	World Bank.
Vulnerability index	Propensity or predisposition of human societies to be negatively impacted by climate hazards.	Notre Dame Global Adaptation Initiative Country Index.
Readiness index	Readiness to make effective use of investments for adaptation actions thanks to a safe and efficient business environment ND-GAIN measures readiness by considering a country's ability to leverage investments to adaptation actions.	Notre Dame Global Adaptation Initiative Country Index.
GAIN index	The ND-GAIN score is constructed by subtracting the vulnerability score from the readiness score for each country, and scaling the scores to give a value 0 to 100.	Notre Dame Global Adaptation Initiative Country Index.
Self-expression score	A value dimension created by running factor analysis. Self-expression values give high priority to environmental protection, growing tolerance of foreigners, gays and lesbians and gender equality, and rising demands for participation in decision-making in economic and political life.	World Value Survey.

TABLE C2— LISTS OF COUNTRIES

Country	Bilateral	Aggregate Weights	lender-loan (conditional on EIR available)	lender-year (conditional on EI available)
Albania			Y	Y
Andorra			Y	Y
Argentina			Y	
Australia	Y	Y	Y	Y

Table C2 continued from previous page

Country	Bilateral	Aggregate Weights	lender-loan (conditional on EIR available)	lender-year (conditional on EI available)
Austria			Y	Y
Azerbaijan			Y	Y
Bahamas			Y	
Bahrain			Y	Y
Bangladesh				Y
Belgium	Y	Y	Y	Y
Bermuda	Y		Y	
Brazil	Y		Y	Y
Brunei			Y	Y
Burundi				Y
Canada	Y	Y	Y	Y
Cayman Islands			Y	Y
Chile			Y	Y
China	Y	Y	Y	Y
Colombia			Y	Y
Cote d'Ivoire				Y
Croatia				Y
Cyprus			Y	Y
Czech Republic			Y	Y
Denmark	Y		Y	Y
Egypt			Y	Y
Fiji				Y
Finland	Y		Y	Y
France	Y	Y	Y	Y
Gabon			Y	Y
Germany	Y	Y	Y	Y
Ghana				Y
Greece			Y	Y
Hong Kong	Y	Y	Y	Y
Hungary			Y	Y
Iceland			Y	
India	Y	Y	Y	Y
Indonesia	Y		Y	Y
Ireland	Y		Y	Y
Israel	Y		Y	Y
Italy	Y	Y	Y	Y
Jamaica			Y	
Japan	Y	Y	Y	Y
Jordan			Y	Y
Kazakhstan			Y	Y
Kenya			Y	
Kuwait			Y	Y
Lebanon			Y	
Luxembourg			Y	Y
Macao			Y	Y
Malaysia	Y	Y	Y	Y
Mauritius			Y	Y
Mexico	Y		Y	Y
Morocco			Y	Y
Netherlands	Y	Y	Y	Y
New Zealand	Y		Y	Y
Nigeria			Y	Y
Norway	Y	Y	Y	Y
Oman			Y	Y
Pakistan			Y	Y
Palestinian Territory			Y	
Panama			Y	Y
Peru			Y	Y
Philippines			Y	Y
Poland			Y	Y

Table C2 continued from previous page

Country	Bilateral	Aggregate Weights	lender-loan (conditional on EIR available)	lender-year (conditional on EI available)
Portugal			Y	Y
Qatar			Y	Y
Romania			Y	Y
Russian Federation			Y	Y
Saudi Arabia			Y	Y
Senegal				Y
Serbia			Y	
Singapore	Y	Y	Y	Y
Slovakia			Y	Y
South Africa	Y		Y	Y
South Korea			Y	Y
Spain	Y	Y	Y	Y
Sri Lanka				Y
Sweden	Y	Y	Y	Y
Switzerland	Y	Y	Y	Y
Taiwan	Y	Y	Y	Y
Thailand			Y	Y
Togo				Y
Tunisia				Y
Turkey	Y		Y	Y
United Arab Emirates			Y	Y
United Kingdom	Y	Y	Y	Y
United States	Y	Y	Y	Y
Vietnam			Y	Y
Zimbabwe				Y

TABLE C3—CORRELATION MATRIX FOR EXPLANATORY VARIABLES

Note: This table presents the correlation between log(GDP per capita) and the alternative explanatory variables behind brown lending resistance explored in Section III.D, including the GAIN index, Readiness index, Vulnerability index, and Self-expression score. The detailed variable definitions are in Table C1.

	log GDP per capita	GAIN	Readiness	Vulnerability
GAIN	0.897			
Readiness	0.822	0.949		
Vulnerability	-0.743	-0.760	-0.517	
Self-expression score	0.714	0.818	0.786	-0.685

TABLE C4—SECTORAL CHANGE: LENDER-LEVEL EVIDENCE II

Note: This table reports estimates from a lender-year-level equivalent of Equation 5.

$$\text{Sectoral weight}_{lKt} = \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_{lt} + \lambda_{lK} + \lambda_{Kt} + \varepsilon_{lKt},$$

where l indexes the (direct) lender, K the sector, and t the year. Standard errors are clustered at the lender level. The dependent variable is the yearly portfolio weight of each sector by a direct lender, computed on the approximated shares in Columns 1 to 3 and on the reported shares in Columns 4 to 6. EI stands for sectoral emission intensity. Log GDP per capita is the logarithm of GDP per capita in current US dollars as a proxy for a country's brown lending resistance. Domestic loans require the borrower country to be the same as the reported lender operating countries. Foreign loans refer to loans where the borrower is not from the lender's operating country or the lender's parent country. The detailed variable definitions are in Table C1. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Sectoral Weight (%) *approximated portfolio*			Sectoral Weight (%) *reported portfolio*		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Domestic	Foreign	Total	Domestic	Foreign
EI X Log GDP per capita	-0.506***	-1.334***	-0.274	-0.603**	-2.083***	0.044
	(0.166)	(0.295)	(0.187)	(0.279)	(0.543)	(0.307)
Constant	14.487***	23.042***	15.470***	19.833***	33.203***	16.556***
	(1.283)	(2.362)	(1.505)	(2.286)	(4.663)	(2.655)
N	58115	27187	29740	32472	13880	17039
Adjusted R2	0.443	0.491	0.401	0.429	0.380	0.391

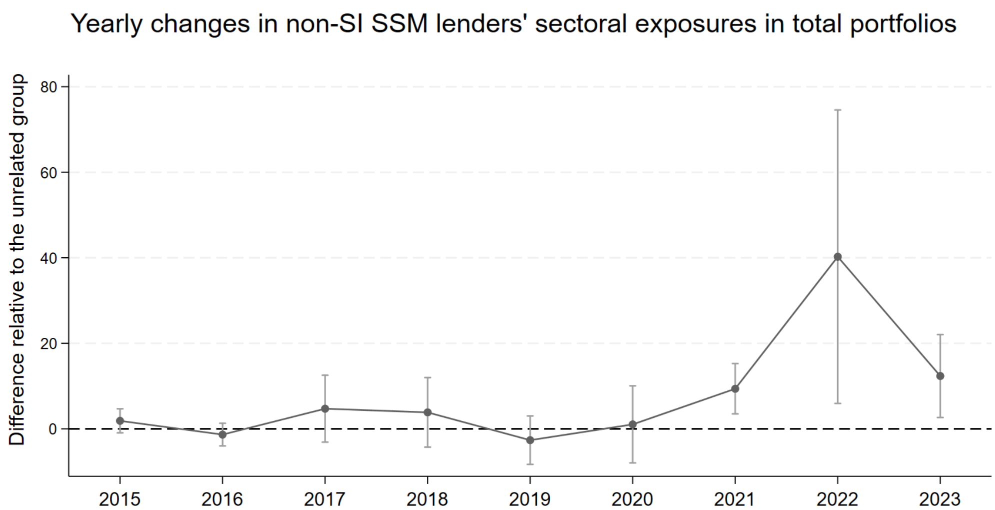

FIGURE C1. ALTERNATIVE ESTIMATES WITH SIS' SECTORAL EXPOSURES OVER 2015 - 2023

This figure describes how the carbon sensitivity based on the sectoral exposures of the SSM-related lenders that are not SIs change over time relative to the control group of "unrelated" lenders. The yearly HDFE estimates are obtained using the equation below:

$$\text{Sectoral Exposure}_{lKt} = \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} + \sum_{t=2015}^{t=2023} \gamma_t \, EI_{Kt-1} \times SI_{lt} \times I_t$$
$$+ \sum_{t=2015}^{t=2023} \theta_t \, EI_{Kt-1} \times Other\ SSM-related\ Lender_{lt} \times I_t + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}.$$

where l indicates lender, b for the loan and t for the year. Standard errors are clustered at the sector and lender level. The control group consists of lenders who are not significant institutions or other SSM-related lenders. The base estimates $EI_{Kt-1} \times I_t$ are absorbed by the fixed effects λ_{Kt}. The plotted estimates show the evolution of θ_t, i.e., how the sectoral exposure of non-SI SSM-related lenders changes over time relative to "unrelated" lenders. The detailed variable definitions are in Table C1. The plotted confidence interval is at the 90% level.

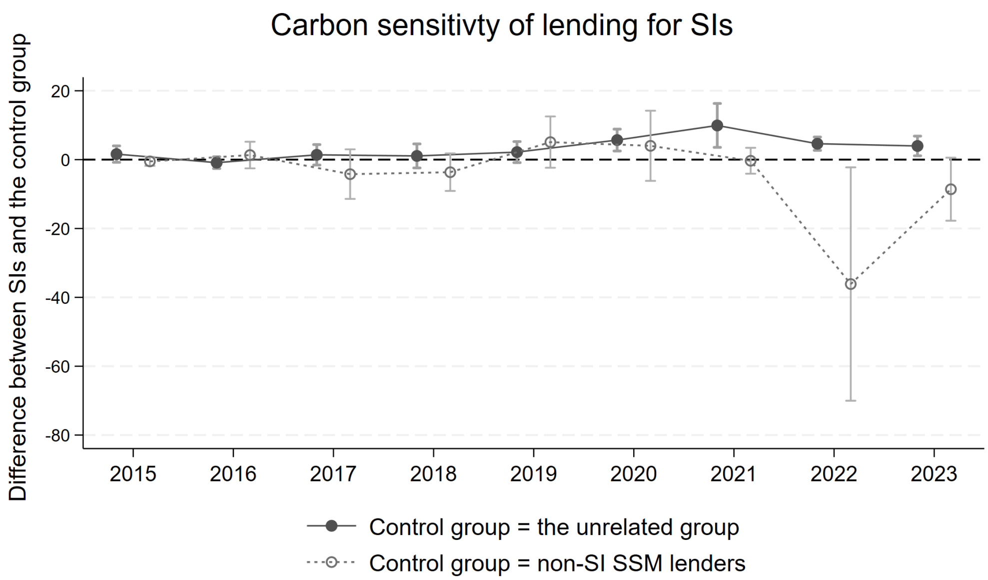

FIGURE C2. ALTERNATIVE ESTIMATES WITH SIS' SECTORAL EXPOSURES OVER 2015 - 2023

This figure plots the yearly estimates based on Equation 8 against those based on Equation 9 regarding the SIs. Specifically, the dotted line plots the estimates γ_t from the following equation:

$$\text{Sectoral Exposure}_{lKt} = \alpha + \sum_{t=2015}^{t=2023} \gamma_t \, EI_{Kt-1} \times SI_{lt} \times I_t + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt},$$

where l indicates lender, b for the loan and t for the year. The associated control group is the SSM lenders that are not SIs. The solid line plots the estimates γ_t from another equation:

$$\begin{aligned}\text{Sectoral Exposure}_{lKt} = \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} + \sum_{t=2015}^{t=2023} \gamma_t \, EI_{Kt-1} \times SI_{lt} \times I_t \\ + \sum_{t=2015}^{t=2023} \theta_t \, EI_{Kt-1} \times \mathit{Other\ SSM-related\ Lender}_{it} \times I_t + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}.\end{aligned}$$

The associated control group consists of lenders who are not related to the SSM region. Standard errors are clustered at the sector and lender level. The detailed variable definitions are in Table C1. The plotted confidence interval is at the 90% level.