International Trade in Brown Loans and The Transfer of Climate-related Risks

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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 to foreign countries, indicating arbitrage and/or incomplete regulations. Furthermore, lenders' climate risk-taking and transfer behaviors vary sharply by syndicate role, loan type, and specialization. Leveraging 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

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Introduction

The role of bank lending in supporting the green transition has only recently gained attention.[1] Climate risks have been increasingly reflected in the loan rates as lenders adjust for higher uncertainty in returns linked to climate exposure.[2] This risk-based pricing raises the cost of capital for carbon-intensive or "brown" firms (Choi et al., 2023; Gormsen et al., 2024; Painter, 2020; Rohleder et al., 2022; Seltzer et al., 2022), but it does not necessarily curb environmental risk-taking among borrowers.[3] Importantly, risk repricing alone doesn't reduce the inherent risk of brown loans or address the societal externalities of such lending. At a given level of brown exposure, both transition risks—arising from the shift to a lower-carbon economy—and physical risks, such as climate-related natural disasters, could lead to higher expected losses due to an increased probability of default or larger loss given default (Ivanov et al., 2023). In fact, rising returns on brown loans may inadvertently increase brown lending exposure among risk-tolerant lenders, raising systemic risk in the financial sector (Battiston et al., 2021; Curcio et al., 2023).

This paper focuses on the exposure to brown firms through the extension of credit. Using global syndicated loan data from 2000 to 2023, I first document how climate-related factors reshape aggregate loan portfolios across countries on the macro level. My estimation suggests a faster shift in the composition of syndicated lending towards greener sectors by more developed countries. A one-standard-deviation increase in GDP per capita is associated with an average 0.71 (0.99) reduction in the total (domestic) portfolio weight of a sector that is one standard deviation higher in emissions intensity, representing 10% (14%) of the pertinent mean sectoral weight.[4] The main implication is that lenders from less developed countries are becoming the main loan financing source for brown sectors globally.

To shed light on how and the extent to which lenders practice climate risk management versus transfers on international markets, I further exploit the within-syndicate variations in share retention. I perform a rich analysis involving potential sales on the secondary markets, loan type participation, lead arranging activities, and foreign lending. In addition to providing extensive evidence on both transfers from more regulated to less regulated players and across borders, I show how lenders' climate risk preferences are related to their role in the syndicate, sectoral specialization, and the exact supervision pressure they receive.

Reducing the weight of brown loans in a lending portfolio directly reduces financial institutions' expected losses from climate risks, but it is often not optimal from lenders' perspectives. Portfolio decisions are based on the relative profitability and riskiness of

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

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

[3] The findings on the real effects following higher costs of capital are mixed. For example, Choi et al. (2020), Houston and Shan (2022), and Rohleder et al. (2022) find improvements in environmental performance by targeted firms, while Davies and Van Wesep (2018) and Hartzmark and Shue (2023) suggest the opposite. Goss and Roberts (2011) find that lenders are indifferent to higher-quality borrowers' environmental decisions, suggesting lenders are not always impact-oriented.

[4] 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.

available projects. Even for a lender with a high willingness to pay for environmental benefits, a brown loan can still be a relatively better deal ex-ante, so the lender has no incentive to forgo it.

Assessing whether and to what extent lenders can reduce brown exposure in response to the domestic supervisory climate and/or the rising awareness is vital for future policy-making. I begin by theoretically modeling international lending decisions across green and brown projects, considering expected returns, diversification needs, and a novel *brown lending resistance* factor inspired by the trade literature. This resistance term captures the extent to which each country's regulatory environment and climate-related preferences inhibit the international flow of brown assets, framed as a measurable barrier to trade in brown loans.

The theoretical framework gives rise to an asset gravity equation that enables comparison across countries and across asset types. I define a measure to capture the relative reduction in the international trade of brown loans, either in terms of amount or weight, given a level of brown lending resistance, specifically *the carbon sensitivity of lending*. The change in the carbon sensitivity of lending with respect to brown lending resistance captures how much lenders effectively reallocate their portfolios away from brown assets in response to a tightening environment.

I derive an empirical model by extending the asset gravity equation for a multi-type case and measuring the "brownness" of each asset type by its emission intensity, i.e., how much a project emits per unit value provided.[5] The subsequent analysis provides evidence for international divergence in the sectoral composition of aggregate loan portfolios.

A few papers have taken a cross-country perspective on bank brown lending and provided micro-level evidence of cross-border credit reallocation. Benincasa (2021) and Benincasa et al. (2022) show that banks increase cross-border lending in response to more stringent domestic climate policies, especially to less regulated countries. They also detect a "relocation" of climate risks where fewer loans are given to domestic brown firms but more to foreign equivalents. Laeven and Popov (2023) show a similar pattern for fossil lending under the introduction of carbon taxes.

Extending this literature, I provide the first macro-level evidence of structural transformation in aggregate international lending portfolios, which effectively takes into account both in-country and cross-country adjustments. My country-level results highlight several climate-related trends in the international lending market over the last two decades. First, on the aggregate level, countries with higher GDP per capita have gone through a faster systematic shift towards sectors with higher carbon productivity (i.e., lower sectoral emission intensity based on value-added) in their aggregate portfolios. With economic development, measured by GDP per capita, being a proxy for brown lending resistance, this result supports my hypothesis of a larger relative reduction in brown loan

[5]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.

trade in countries with higher brown lending resistance (*high-resistance* countries). The finding is robust against including possible omitted variables other than GDP per capita in the proxy process for brown lending resistance.

Second, there exists a persistent gap in how domestic and foreign carbon sensitivities respond to brown lending resistance. I refer to it as *the domestic-foreign carbon wedge*.

Within the theoretical framework, a larger domestic response is expected to the extent that higher economic development may have reduced the domestic carbon premium and loan demand from browner sectors, causing the portfolio weight of domestic brown loans to decrease more naturally. However, yearly estimates contrasting the dynamic changes in domestic and foreign portfolios show strong signs of regulatory arbitrage flows, where lenders seem to actively adjust their international lending portfolios to cope with the anticipation and revelation of regulatory tightening.

Third, the observed sectoral shift in aggregate lending portfolios is attributed to multiple country characteristics. I decompose the aggregate effect along three channels. A high-resistance country benefits 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. Evidence suggests that the observed market outcomes are co-shaped by these three aspects, with pairwise strong correlations among themselves and with economic development.

The main observations are further tested on the micro level with lenders' reported shares and firm-level emission intensities. I focus on the effect of brown lending resistance on lending decisions by controlling the confounding effect of economic development on loan demand and loan return with additional deal-level fixed effects. Conforming to the prediction that lenders from high-resistance countries tend to reduce brown exposure more actively, my results are consistent with the findings on banks' exposure management for climate risks by, for instance, 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).

At the intensive margin, foreign carbon sensitivity also significantly increases with brown lending resistance. On the one hand, it demonstrates a rising awareness of climate risks and associated reduction in risk exposure among banks as the GDP per capita of their home country increases. On the other hand, it implies that increasing shares in global brown deals are gradually being transferred to investors from low-resistance countries. This second implication especially highlights the importance of a global perspective on sources of carbon financing and the importance of global policy coordination.

Apart from exposure reduction, banks have been found to manage climate risks by increasing credit line lending and shortening maturity, which is accompanied by higher participation of shadow banks and more brown lending abroad (Benincasa, 2021; Benincasa et al., 2022; Bruno & Lombini, 2023; Ivanov et al., 2023; Laeven & Popov, 2023; Miguel et al., 2024). My paper provides evidence for both types of risk transfers: from more regulated to less regulated lenders and from more regulated to less regulated areas. The key evidence is that the response of carbon sensitivity to brown lending resistance is weaker in loans that are more suitable to sell on the secondary market, stronger among

lenders who mostly keep their shares on the balance sheets, and, in general, weaker when dealing with foreign borrowers.

This paper expands this line of literature by revealing how lenders' climate risk-taking and climate risk management can depend on their roles in the syndicate. Understanding how increased brown lending resistance affects lead arranging activities is 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).

A comparison between lead arrangers and other underwriting agents allows me to remove the impact of information asymmetry. I find that lead arrangers retain a larger share in browner loans than other agents who are involved in the underwriting process.

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). They often have to retain the residual demand if the deal is "cold" — a pipeline risk addressed by Bruche et al. (2020). Therefore, apart from a greater need for quality signaling, larger brown retention by lead arrangers may be caused by a smaller demand for brown loans by other lenders, which I call a *climate pipeline risk* hypothesis.

By comparing credit lines and term loans, I show a significant difference in lead arrangers' share retention between the two types of loans. In credit lines, although lead arrangers tend to retain a larger share than other lenders, this extra retention is not sensitive to the borrower's brownness. However, in term loans, lead arrangers significantly increase their retention for browner firms, and this increase is smaller for lead arrangers from countries with higher economic development. The finding is consistent with the climate pipeline risk hypothesis. With the trend that participants demand more credit line shares than term loans when dealing with a brown borrower, lead arrangers face a more severe pipeline risk in term loans. This new finding suggests the complexity of risks that banks may face during the net-zero transition.

Further investigating their share retention in foreign loans, I obtain two novel observations. First, lead arrangers adjust their domestic and foreign portfolios in an overall consistent manner. Second, these non-lead lenders from high-resistance countries decrease shares in brown loans abroad by significantly less than domestically, exclusively through credit lines. The two observations together indicate that arbitrage transfers are mainly carried out by non-lead lenders through credit lines.

The direct lending outcomes also depend on the lending preferences of their parents. For instance, parent lenders can use their foreign subsidiaries to expand brown credits (Demirgüç-Kunt et al., 2024). 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 find that banks respond to home countries' brown lending resistance by reducing more of their foreign brown exposure, while non-banks are not responsive at all. This provides direct evidence for the risk transfer to less regulated lenders. Moreover, lenders in a weaker capital position show consistent exposure reductions in both domestic and

foreign portfolios, while those with stronger capitalization show even stronger retrenchment from brown loans in their domestic portfolio but no sign of foreign adjustment. This sharp disparity adds to the evidence for a cross-border relocation of climate risks.

What makes some lenders more prone to transfer risk to foreign markets? Laeven and Popov (2023) propose a role in foreign fossil lending. 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 provide direct support for a generic role of sector-specific specialization in cross-border credit reallocation. 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.

Having shown comprehensive evidence for climate risk transfers and the role of lender specialization, I continue with the question of how inappropriate climate banking supervision might fuel carbon leakage.

Several papers have discussed different aspects of climate banking supervision. While theoretical results overall favor carbon taxes over financial intervention (Döttling & Rola-janicka, 2022; Oehmke & Opp, 2022), several papers have shown that the introduction of country-specific carbon taxes and a gap in climate policy stringency internationally causes carbon leakage through financial markets (Benincasa, 2021; Benincasa et al., 2022; Ivanov et al., 2023; Laeven & Popov, 2023). This suggests room for financial intervention.

The difficult question is then what type of financial intervention may be helpful. 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.

This paper contributes to this growing body of literature on climate banking supervision by showing the potential issue with a common banking supervisory measure — supervisory expectations. Exploiting the publication of the ECB Guide on climate-related and environmental risks for banks (*the Guide*) in November 2020, I find that a soft measure with supervisory disparity can backfire.

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. The international data allow me to address the concern that the other lenders within this supervisory area may be reversely affected simultaneously, and using them as the control group leads to a biased policy evaluation. I argue that a more valid control group is the international lenders that are

unrelated to European banking supervision, rendering both significant institutions and other lenders "treated" (but in different ways) under the shock of the Guide.

The evaluation outcome is turned around in this global exercise. 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. The previously observed drop in brown lending by directly supervised banks is attributed to the faster brown credit expansion among the "unintended" group, which is a direct consequence of unequal supervision. My finding is in line with Miguel et al. (2024), who document an expansion effect for smaller banks that are not targeted.

By revealing a different perspective of ECB's climate guide, this paper contributes to a broader discussion on financial regulation. 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 documentation of various forms of risk transfers and adverse effects of supervisory expectations calls for more discernment in macro-prudential policymaking.

Is it always better to have some supervisory measures than none? 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.

Lastly, this paper relates to the literature on global capital allocation and international trade of assets. Institutional factors and regulatory differences have been established determinants of international capital flows by, for example, Di Giovanni (2005), Florez-Orrego et al. (2023), Houston et al. (2012), and Karolyi and Taboada (2015). Recent studies start incorporating climate risks in explaining, for example, of foreign direct investment (Gu & Hale, 2023) and equity holding (Benink et al., 2024). This paper showcases a climate-related extension of the asset trade model following Aviat and Coeurdacier (2007) and presents how the disparity in climate-related preferences shifts international bank lending flows in a structured way.

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 risk-averse 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 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 incurs a total cost of $p_{ij} = p_j \tau_{ij}$ for financing a share in a project from the borrowing (or destination) country j, where τ_{ij} is an iceberg transaction cost that features the frictions on international financial markets 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, which can arise from the pro-environmental preference of the representative bank or that of its domestic supervisor.

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 perfectly diversified portfolio.

A project in destination country j run by household h pays off d_{qj} only when the project's realized state h_j matches the 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. The combination of stochastic realization and an incomplete market

gives rise to a perfectly 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.

Assume the two countries have different levels of economic development, which is directly reflected in the wealth endowment y_i. I refer to the country with a higher economic development level as Country H (and domestic country) and the other country as Country L (and foreign country). The representative bank of Country H (hereafter Bank H) chooses $\{x_h^H\}_{h\in\{1,\dots,n_1\}}$, domestic loan amounts, and $\{x_k^L\}_{k\in\{1,\dots,n_2\}}$, foreign loan amounts, with minimum reserves. Formally, Bank H maximizes its profit as follows:

$$
\begin{aligned}
&\max_{\{\{x^H\},\{x^L\}\}} \left\{ \mathbf{E}\left(\frac{D_H^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \right) \right\} \\
&\text{s.t.} \quad \sum_{k=1}^{n_L} p_L \tau x_k^L + \sum_{h=1}^{n_H} p_H x_h^H \leq n_H y_H (1-s_H)
\end{aligned} \tag{1}
$$

with $\sigma > 1$ for standard imperfect substitution, and τ as a simplification of τ_{12}.

The within-country price homogeneity for each type of project implies $x_k^L = x_C^L$ for all type-C projects and $x_k^L = x_D^L$ for all type-D projects provided by the foreign country, and domestically $x_h^H = x_C^H$ for all type-C projects and $x_h^H = x_D^H$ for all type-D projects. I then derive the first order conditions with respect to x_C^H, x_C^L, x_D^H and x_D^L to obtain the optimal per-project share x_C^H, x_D^H, x_C^L and x_D^L.[6]

Denote the Lagrange multiplier for the budget constraint with λ_H. I aggregate the values of the per-project shares over the total projects to obtain the lending values to domestic-clean (*HC*), domestic-dirty (*HD*), foreign-clean (*LC*), and foreign-dirty (*LD*) projects:

$$
\begin{aligned}
\mathbf{X}_C^H &= p_H \pi_H n_H x_C^H = p_H \pi_H n_H \frac{{d_C^H}^{\sigma-1}}{(L\lambda_H p_H)^\sigma} \\
\mathbf{X}_D^H &= p_H (1-\pi_H) n_H x_D^H = p_H (1-\pi_H) n_H \frac{(d_D^H \theta_H)^{\sigma-1}}{(L\lambda_H p_H)^\sigma} \\
\mathbf{X}_C^L &= p_L \tau \pi_L n_L x_C^L = p_L \tau \pi_L n_L \frac{{d_C^L}^{\sigma-1}}{(L\lambda_H p_L \tau)^\sigma} \\
\mathbf{X}_D^L &= p_L \tau (1-\pi_L) n_L x_D^L = p_L \tau (1-\pi_L) n_L \frac{(d_D^L \theta_H)^{\sigma-1}}{(L\lambda_H p_L \tau)^\sigma}
\end{aligned} \tag{2}
$$

[6]The detailed derivation is provided in Appendix A.

Denote the expected net returns: $R_C^j = \frac{d_C^j}{Lp_j}$ and $R_D^j = \frac{d_D^j}{Lp_j}$. The budget constraint must bind, yielding:

$$\begin{aligned} & \mathbf{X}_C^H + \mathbf{X}_D^H + \mathbf{X}_C^L + \mathbf{X}_D^L \\ = \quad & \frac{\pi_H n_H (R_C^H)^{\sigma-1} + (1-\pi_H) n_H (R_D^H \theta_H)^{\sigma-1} + \pi_L n_L (R_C^L/\tau)^{\sigma-1} + (1-\pi_L) n_L (R_D^L \theta_H/\tau)^{\sigma-1}}{L\lambda_H^\sigma} \\ = \quad & (1-s_H) n_H y_H \end{aligned}$$

Define the project-type-specific return indexes, $\bar{R}_C \equiv \frac{\pi_H n_H}{M_C}(R_C^H)^{\sigma-1} + \frac{\pi_L n_L}{M_C}(R_C^L)^{\sigma-1}$ and $\bar{R}_D \equiv \frac{(1-\pi_H) n_H}{M_D}(R_D^H)^{\sigma-1} + \frac{(1-\pi_L) n_L}{M_D}(R_D^L)^{\sigma-1}$, and additionally a foreign return index $\bar{R}^L = \frac{\pi_L n_L}{n_L}(R_C^L)^{\sigma-1} + \frac{(1-\pi_L) n_L}{n_L}(R_D^L \theta_H)^{\sigma-1}$. The Lagrangian multiplier λ_H can be solved from:

$$\lambda_H^\sigma = \frac{\frac{M_C}{L}\bar{R}_C + \frac{M_D}{L}\theta_H^{\sigma-1}\bar{R}_D - (1-\tau^{1-\sigma})\frac{n_L}{L}\bar{R}^L}{(1-s_H) n_H y_H}$$

Index the aggregate return of Country H's portfolio with $\mathbf{R^H} = \frac{M_C}{L}\bar{R}_C + \frac{M_D}{L}\theta_H^{\sigma-1}\bar{R}_D - (1-\tau^{1-\sigma})\frac{n_L}{L}\bar{R}^L$. Substituting λ_H back to Equation 2, Country H's aggregate lending to domestic-clean (*HC*), domestic-dirty (*HD*), foreign-clean (*LC*), and foreign-dirty (*LD*) projects are given by:

$$\begin{aligned} \mathbf{X}_C^H &= \frac{\pi_H n_H}{L}\,(1-s_H) n_H y_H\,\frac{(R_C^H)^{\sigma-1}}{\mathbf{R^H}} \\ \mathbf{X}_D^H &= \frac{(1-\pi_H) n_H}{L}\,(1-s_H) n_H y_H\,\frac{(R_D^H \theta_H)^{\sigma-1}}{\mathbf{R^H}} \\ \mathbf{X}_C^L &= \frac{\pi_L n_L}{L}\,(1-s_H) n_H y_H\,\frac{(R_C^L/\tau)^{\sigma-1}}{\mathbf{R^H}} \\ \mathbf{X}_D^L &= \frac{(1-\pi_L) n_L}{L}\,(1-s_H) n_H y_H\,\frac{(R_D^L \theta_H/\tau)^{\sigma-1}}{\mathbf{R^H}} \end{aligned} \tag{3}$$

The type-specific domestic and bilateral lending flows follow a general gravity form, including a supply factor capturing the size of one project type in the destination country, such as $\pi_L n_L$ in $\mathbf{X}_C^L$, a demand factor capturing the available capital, e.g., $n_H y_H$, a return factor, e.g., ${R_C^L}^{\sigma-1}/\mathbf{R^H}$ and lastly the frictions, e.g., $\tau^{\sigma-1}$. For brown lending X_D^H and X_D^L, there is a brown lending resistance term ${\theta_H}^{\sigma-1}$, specific to the lending country.

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

$$\begin{aligned} W_{HC} &= \frac{\pi_H n_H}{L}\frac{(R_C^H)^{\sigma-1}}{\mathbf{R^H}} \;\;\&\;\; W_{HD} = \frac{(1-\pi_H) n_H}{L}\frac{(R_D^H \theta_H)^{\sigma-1}}{\mathbf{R^H}} \\ W_{LC} &= \frac{\pi_L n_L}{L}\frac{(R_C^L/\tau)^{\sigma-1}}{\mathbf{R^H}} \;\;\&\;\; W_{LD} = \frac{(1-\pi_L) n_L}{L}\frac{(R_D^L \theta_H/\tau)^{\sigma-1}}{\mathbf{R^H}} \end{aligned} \tag{4}$$

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

$$
\begin{aligned}
\mathbf{X}_C &= \mathbf{X}_C^H + \mathbf{X}_C^L = \frac{M_C}{L}\frac{(1-s_H)n_H y_H}{\mathbf{R^H}}[\bar{R}_C - \frac{\pi_L n_L}{M_C}(1-\tau^{1-\sigma})R_C^{L\,\sigma-1}], \\
\mathbf{X}_D &= \mathbf{X}_D^H + \mathbf{X}_D^L = \frac{M_D}{L}\frac{(1-s_H)n_H y_H}{\mathbf{R^H}}\theta_H^{\sigma-1}[\bar{R}_D - \frac{(1-\pi_L)n_L}{M_D}(1-\tau^{1-\sigma})R_D^{L\,\sigma-1}].
\end{aligned} \tag{5}
$$

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

$$
\begin{aligned}
W_C &= \frac{X_C}{(1-s_H)n_H y_H} = \frac{M_C}{L}\frac{\bar{R}_C - \frac{\pi_L n_L}{M_C}(1-\tau^{1-\sigma})R_C^{L\,\sigma-1}}{\mathbf{R^H}}, \\
W_D &= \frac{X_D}{(1-s_H)n_H y_H} = \frac{M_D}{L}\theta_H^{\sigma-1}\frac{\bar{R}_D - \frac{(1-\pi_L)n_L}{M_D}(1-\tau^{1-\sigma})R_D^{L\,\sigma-1}}{\mathbf{R^H}}.
\end{aligned} \tag{6}
$$

To compare the lending between the two types of projects, I define the **carbon sensitivity of lending**.

Definition 1. *The bilateral carbon sensitivity of lending is defined as*

$$
log(\frac{X_C^j}{X_D^j}) = log(\frac{\pi_j}{1-\pi_j}) + (\sigma-1)(logR_C^j - logR_D^j) - (\sigma-1)log\theta_H, \ \textit{for } j \in \{H,L\}
$$

The same equation holds for the ratio of weights. It measures the extent to which a country allocates more capital toward clean projects than to dirty projects domestically ($j = H$) or abroad ($j = L$).

A similar equation holds when comparing the aggregate allocation of capital between clean and dirty projects with more complicated return terms. The carbon sensitivity of lending generally depends on three components: the relative fraction of the two types, the relative expected net return, and a climate supervision adjustment. 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 that has access to the international market of loans.

Proposition 1. *If brown lending resistance increases (represented by a smaller θ), ceteris paribus, the country will have a higher carbon sensitivity of lending.*

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]

[7]In general, the relative carbon sensitivity of lending between two countries depends on three factors: the relative

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

This proposition considers how much $\frac{W_C^H}{W_D^H}$ and $\frac{W_C^L}{W_D^L}$ are affected by θ_H, 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.

Proposition 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 Proposition 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).

B. Multi-type extension and empirical model

The baseline model considers two broad types of projects. To extend Equation 3 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.

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.

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:

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

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 $\frac{\partial \log(X_{K_j}^i)}{\partial \eta_K}$ 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:

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

To construct an empirical identification equation, observe that $\frac{\partial \log(X_{K_j}^i)}{\partial \eta_K}$ 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:

$$\frac{\partial \log(X_{K_j}^i)/\partial \eta_K}{\partial \log(\text{GDP per capita}_i)} = (\sigma-1)\frac{\partial \log\theta_i}{\partial \log(\text{GDP per capita})_i} = \mu(\sigma-1), \tag{7}$$

where μ represents the quantitative relationship between log(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:

$$X_{i,j,t}^K = Exp\left[\alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{it-1} + \lambda_{ij} + \lambda_{it} + \lambda_{Kjt}\right]\varepsilon_{ijt} \tag{8}$$

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, in reality, there can be a transfer of brown lending 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 7 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 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 (2021) and Ginglinger and Moreau (2023). Bolton and Kacperczyk (2021) show weak evidence that firms in countries with higher GDP per capita have smaller short-term carbon premiums in stock markets. Ginglinger and Moreau (2023) suggests that brown firms reduce their demand for debt without examining how this tendency is related to economic development.[8] 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 8 measures how the semi-elasticity of lending with regard to emission intensity changes as income per capita rises. It cannot be interpreted as a level change in lending. To facilitate the interpretation, I use the level variables in linear regressions for the subsequent tests.

[8] 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.

II. Data, variables, and statistics

This section summarizes the data sources and constructed variables used in the empirical analysis.[9] 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 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.

Assuming that the empirical relationship between post-origination holdings and reported shares that Blickle et al. (2020) concluded from mapping US regulatory fillings (the Shared National Credit) to the LPC DealScan data 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 observa-

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

tions 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 sell-off 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:

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

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,

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

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

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

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.[10] 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 "Agent".[11] 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:

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

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

[11] 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".

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.

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.[12]

One important assumption for the empirical identification using Equation 8 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.[13]

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

[12]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.

[13]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.

sectors' emission intensities internationally, with 10 out of the 12 countries having the same ranking as the UK.[14]

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.[15] 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.

C. Other data

The other data include 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***). In other words, the Vulnerability and Readiness Indexes measure, respectively, the physical conditions and exposure to climate change of a country and its investment availability for climate actions. 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

[14] 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.

[15] 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.

assistance needs, or less significant institutions (LSI) if they do not meet significance criteria.[16] I collected the lists of supervised entities from the ECB website, which have been maintained regularly since the start of 2015.[17]

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 describe this in detail 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.

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.[18] 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 country number 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

[16]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.

[17]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.

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

portfolios of at least some country for 20 years or more.

I also constructed 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, 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 RCAs.

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.[19] 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

[19] About 22% of the lender-year observations were excluded due to this frequency criterion.

observation.

A. Country-level baseline results

I test for the relationship between economic development and carbon sensitivity of lending with the bilateral flows, following the gravity model in Equation 8. To exploit the information in the zeros as well, I use the Poisson Pseudo-Maximum Likelihood (PPML) estimator (Silva & Tenreyro, 2006).[20]

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

$$(9)\quad \text{Sectoral weight}_{iKt} = \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{it-1} + \lambda_{iK} + \lambda_{it} + \lambda_{Kt} + \varepsilon_{iKt}$$

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

This linear regression specification is different from the baseline gravity specification 8 in two ways. First, it is taken to the linear form without log transforming the dependent variable for more meaningful interpretation while keeping the intended zeros. The estimated coefficient can then be translated into a direct level change in the sectoral weights of country loan portfolios.[21] 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.[22] 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

[20] I estimate all other equations in this paper using the high-dimensional fixed effects (HDFE) estimator by Correia (2017).

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

[22] 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.

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.

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 emerged more prominently 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. It is possible that some borrowers turned to debt financing as the stock market responded more timely to the Paris Agreement, contributing to the domestic rebound observed 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 inform a view of the market clearing outcomes. Individual lenders can have different approaches to climate risk management, such as exposure reduction or more active monitoring of carbon performances. 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 9, 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 the baseline specification 9 the interaction terms of EI with, respectively, bank deposits to GDP, bank concentration (asset share of 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, the 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 the 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 de-

creasing 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 the carbon-intensive sectors and have more resources for sector-specific adaptation, which leads to a higher propensity for low-carbon transformation of the economic structure. Second, the 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 of being damaged by climate hazards. The latter is featured by lower dependency on climate-sensitive sectors, better physical capacity in handling the possible climate damages on demography and 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 the attitudes toward climate issues, following Gantchev et al. (2022). Countries with more pro-environmental cultures and values may provide more finance to the 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 the 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 the faster sectoral changes in the loan portfolios in countries with

high economic development. Next, I additionally test if the 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 the 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.[23]

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.[24] 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 the syndicated loan markets. The within-syndicate variations I use for the following sections facilitate the interpretation through brown lending resistance. The sectoral loan demand differences would not be an issue when I examine the intensive margin decisions using firm-level emission intensities, and the return differences will be controlled at the deal level.

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 the effects through 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 the loan and lender heterogeneity.

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

[24] *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.

A. *Lender-loan-level baseline results*

Exploiting the between-lender variations in the 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:

$$\text{Loan share}_{lbt} = \alpha + \beta EIR_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt}, \tag{10}$$

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

This specification considers the 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 the 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 the 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 10 with small share lenders that report a share below 30%.

The estimates concerning the 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 prefer-

ences. 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 the small share lenders are similar to the lender-loan baseline estimate, while the estimates associated with foreign portfolios are slightly different. Considering only the 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 the specification 9 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 the 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 and Kahn (2022).[25] 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, the larger share lenders are more likely to be lead arrangers, while the 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

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

nonlead participants from countries with different levels of brown lending resistance, as well as their foreign lending preferences.

Blickle et al. (2020) also suggests 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 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 10, 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 arranger's larger retention. First, the lead arranger's 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, the 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 the non-lead lenders become more concerned with climate risks, the lead arrangers are more incentivized to hold larger shares to signal. 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) documents 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 reten-

tion 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 the 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 the 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 when taking into consideration the extensive margin changes.[26] 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

[26]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.

loans separately, where I again distinguish between lead arrangers and the others. 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 the others 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 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 the browner loans, while the 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 the lending opportunities.

The second cause behind the domestic-foreign wedge is that a country's brown lending resistance does not equally impact all the domestic lenders in reality. The selloff problem discussed previously is an example of how the brown loans may have been transferred to the 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 9 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 is 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 that overall better-capitalized lenders 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 the 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 the foreign loans only, the estimate is similar in size but more significant. This implies that banks

respond to higher domestic brown lending resistance with more 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 that are subject to capital requirements, consisting of banks and some other financial institutions. I define weak lenders to be ones 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.

For the better-capitalized lenders, the all-loan estimate is significantly negative, as shown in Column 5. The size of 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.[27] 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 the portfolios with foreign ones, i.e., "relocation" of brown loans.[28] This provides an important aspect of climate policy spillovers.

It is unclear what consequences these reallocation activities may have on lenders' per-

[27]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.

[28]The difference in the all-loan estimates between weak and non-weak lenders supports this interpretation. Banks with higher capital levels have been previously 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.

formances. 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 the 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 look into the 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.

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 is 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.[29] 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:

$$\begin{aligned}\text{Total share}_{lbt} = {} & \alpha + \beta\ EI_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \gamma_1\ RCA_{lt-1} \\ & + \gamma_2\ RCA_{lt-1} \times EI_{bt-1} + \gamma_3\ RCA_{lt-1} \times \log(\text{GDP per capita})_{lt-1} \\ & + \gamma_4\ RCA_{lt-1} \times EI_{bt-1} \times \log(\text{GDP per capita})_{lt-1} + \lambda_{bt} + \lambda_{lt} + \varepsilon_{lbt},\end{aligned} \tag{11}$$

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 the 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 the more opaque firms.

As in the baseline specification, β measures how a lender's carbon sensitivity of lending changes with the level of home-country brown lending resistance. Additionally, this specification 11 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 the 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 the increasing brown lending costs.

Table 10 summarizes the results. Columns 1 and 2 first provide the baseline results

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

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 11 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, the RCAs based on the reported shares may underestimate the brown specialization if banks intentionally underreport their participation in brown loans. To mitigate this concern, I constructed the alternative RCAs based on the 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 the 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 in which the borrower operates. 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 the dynamic regulatory changes within a country or a region.

According to the theoretical framework of this paper, a climate supervision measure that targets all the 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 the lenders equally. One such example is the Single Supervisory Mechanism (SSM), whereby the European Center 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.[30]

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.[31]

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 the SIs and LSIs how the ECB expects them to understand the 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 the direct supervision practices for SIs, leading to a disparity in climate supervision. The ECB started directly monitoring the climate management progress of the SIs as soon as the Guide was published. The LSIs are left to their national competency authorities, who are in different stages of

[30]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.

[31]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.

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 the 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.[32]

How would the formal supervisory expectations change the brown lending by the 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 has 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 the SIs.

Concerning the rule-based climate supervision measure taken by Brazil in 2017, Miguel et al. (2024) finds the targeted banks to reallocate credits away from the 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 the non-SI lenders. Specifically, I hypothesize that the weak supervision and supervisory disparity implied by the Guide would lead to little reduction of brown lending of 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.[33] I estimate the following triple difference-in-difference (DDD) specification at the direct lender level:

$$\begin{aligned}\text{Sectoral Exposure}_{lKt} =& \alpha + \gamma_1 EI_{Kt-1} \times SI_{lt} + \gamma_2 EI_{Kt-1} \times SI_{lt} \times Post\ Guide_t \\ &+ \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt},\end{aligned} \tag{12}$$

where l indicates lender, K for the sector and t for 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 the dependent variables.[34]

I do not include the baseline interaction term of $EI \times \log$GDP per capita here because I focus on the 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 the general supervisory intensity was correlated with sectoral exposure before the shock, and γ_2 re-

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

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

[34]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.

veals 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 the 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 "untreated" in effect. If the Guide unintentionally relieves the climate-related supervisory burden faced by the 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 the 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 Lender*. This group of lenders are most likely "beneficiaries" of the Guide. If they expected stricter measures before, the soft supervision and the unequal implementation revealed by the 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.

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

$$\begin{aligned}\text{Sectoral Exposure}_{lKt} = {} & \alpha + \beta EI_{Kt-1} \times \log(\text{GDP per capita})_{lt-1} \\ & + \gamma_1 EI_{Kt-1} \times SI_{lt} + \gamma_2 EI_{Kt-1} \times SI_{it} \times Post\ Guide_t \\ & + \gamma_3 EI_{Kt-1} \times Other\ SSM-related\ Lender_{lt} \\ & + \gamma_4 EI_{Kt-1} \times Other\ SSM-related\ Lender_{lt} \times Post\ Guide_t \\ & + \lambda_{lK} + \lambda_{lt} + \lambda_{Kt} + \varepsilon_{lKt}.\end{aligned} \tag{13}$$

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 here.

The control group changes when moving from Specification 12 to Specification 13. 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.[35] 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 12.

[35]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.

I report the estimation results in Table 11, with Columns 1 to 3 for the first test using Specification 12 and Columns 4 to 6 for the second test using Specification 13. 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 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 the SIs and other SSM-related lenders, to a third group consisting of the unrelated lenders. The baseline result related to $EI \times \log$GDP per capita remains the same as in the previous analyses. However, the results regarding the post-shock changes are completely different from this broader perspective.

I highlight two key deviations when taking the unrelated lenders as the control group instead of the 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 have started to show significant differences in their carbon sensitivity when lending only during 2020. [36]

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. [37]

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

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

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 the credits across borders through the 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

Climate change is a global issue requiring international cooperation. A country's effort to reduce emissions can be undone by another country's lack of action, as the likelihood of climate disasters depends on global emissions. This coordination challenge can be further complicated with the involvement of financial markets.

In this paper, 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 estimation provides 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. On the other hand, 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 the adverse shocks subsequently due to financial contagion.

Exploiting the share retention variations at the intensive margin, I 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, 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 the 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. On the other hand, 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. 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 efficient.

I additionally show two important drivers of risk transfers. Lending specialization in brown sectors explains a great deal of the associated cross-border credit reallocation. The other key component involves the supervisory signal. 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. How banks react to such expectation-based measures is consistent with a risk-taking channel that has been identified in the context of macroeconomic policy transmission (Borio & Zhu, 2012), i.e., the impact of the policy change on risk-taking or risk tolerance, and worth more attention for future research.

TABLE 1—SUMMARY STATISTICS FOR COUNTRY-LEVEL SAMPLES

Note: This table reports the 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 the 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 8, 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 9, considering the lenders with nonzero lending for more than 12 years 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 the 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 9 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 the 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 9 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 the 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 10 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 the 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 10. 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 the 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	-0.996***				
Log GDP per capita	(0.238)				
Agent X	0.121				
EIR X Log GDP per capita	(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		-0.279	-0.741*	0.735	
Log GDP per capita		(0.461)	(0.440)	(0.473)	
Lead Arranger X		-0.937**	0.193	-1.182***	
EIR X Log GDP per capita		(0.451)	(0.258)	(0.421)	
Term Loan X					0.497*
Log GDP per capita					(0.263)
Term Loan X					-1.313***
EIR X Log GDP per capita					(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 10 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 the 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 Arrangers	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 10 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 ones that are not. Columns 4 and 5 contrast parent lenders that are weak with ones that are not. Weak lenders are those whose Tier 1 capital ratio is within the bottom 25% percentiles. EIR stands for the 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 11. 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 the 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***	-0.051*	-0.122***	-0.091***	-0.105***	-0.110***
	(0.031)	(0.030)	(0.037)	(0.034)	(0.037)	(0.035)
RCA			0.407*	0.498**	0.516***	0.737***
			(0.235)	(0.230)	(0.198)	(0.180)
EI X RCA			-0.131*	-0.216***	-0.095	-0.339***
			(0.073)	(0.065)	(0.099)	(0.098)
Log GDP per capita X RCA			-0.033	-0.037	-0.038*	-0.060***
			(0.022)	(0.024)	(0.019)	(0.018)
EI X Log GDP per capita X RCA			0.013*	0.022***	0.013	0.035***
			(0.008)	(0.007)	(0.010)	(0.011)
Constant	15.313***	10.988***	15.708***	11.509***	15.503***	11.704***
	(0.258)	(0.267)	(0.309)	(0.314)	(0.309)	(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 12 and 13. 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 the total loans, Columns 2 and 5 considering the domestic loans, and Columns 3 and 6 considering the 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 the 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

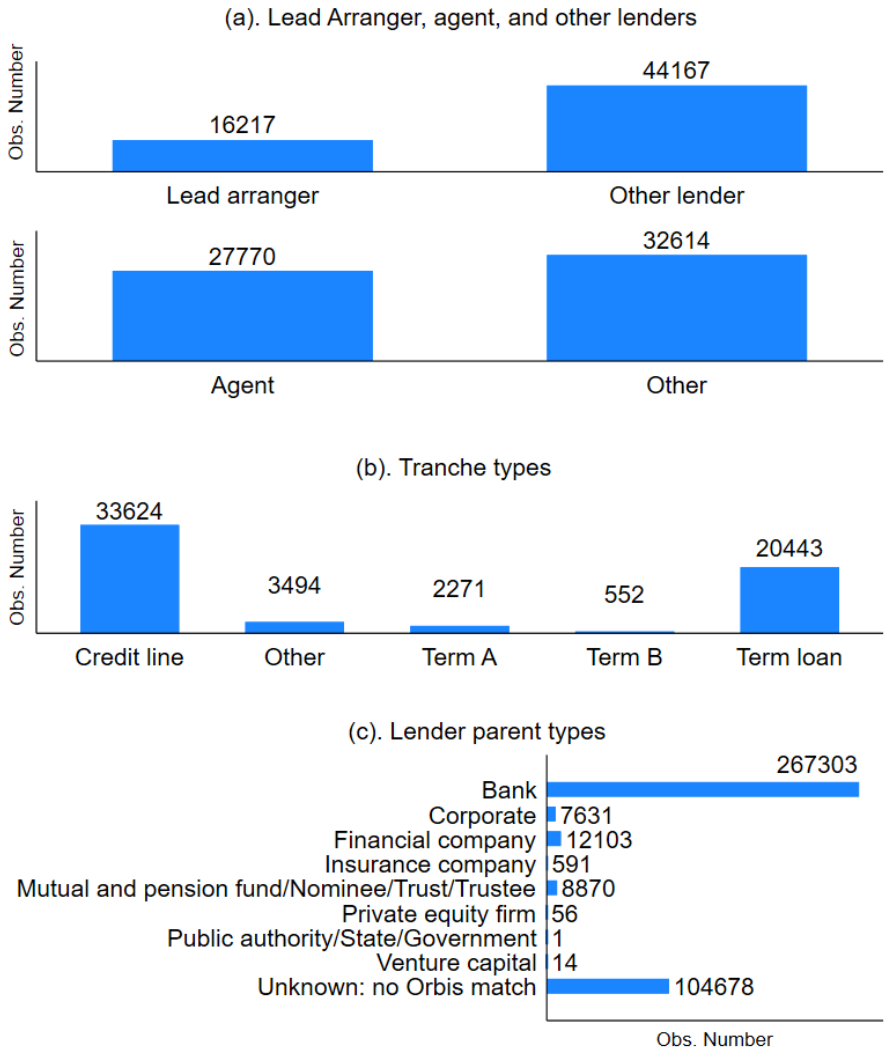


FIGURE 1. SUMMARY OF LENDER ROLES AND LOAN TYPES

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.

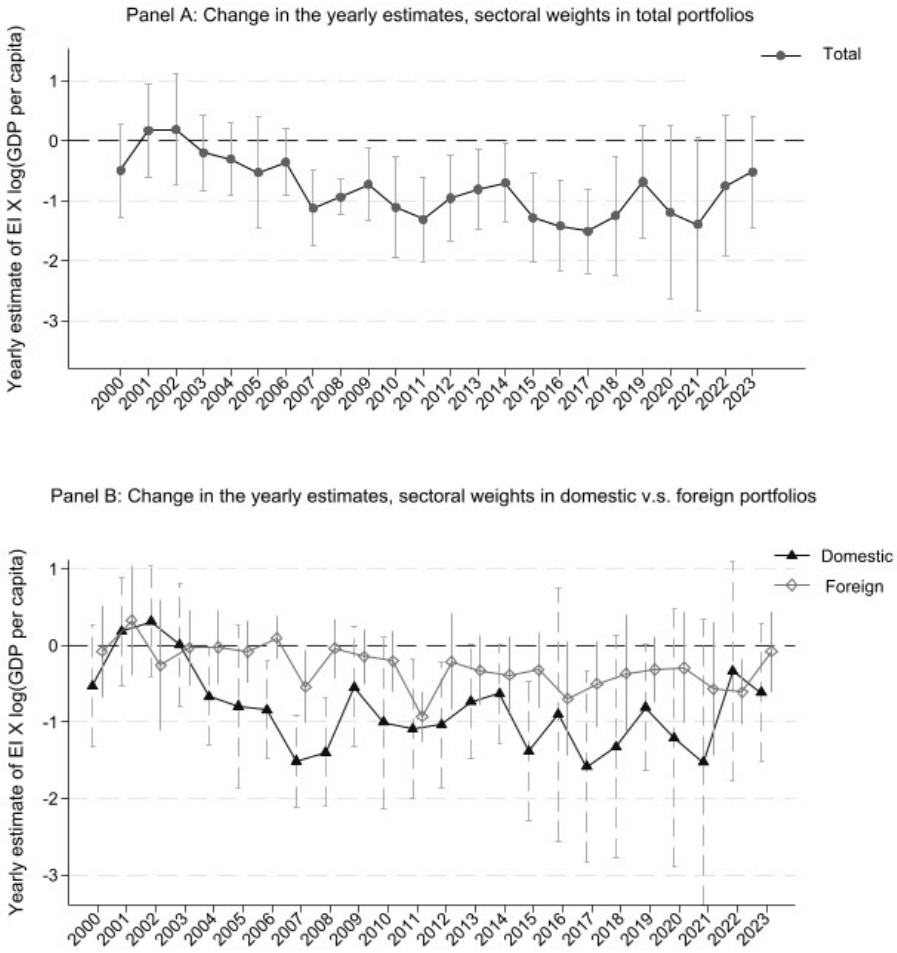


FIGURE 2. ESTIMATES WITH PORTFOLIO WEIGHTS OVER 2001 - 2023

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.

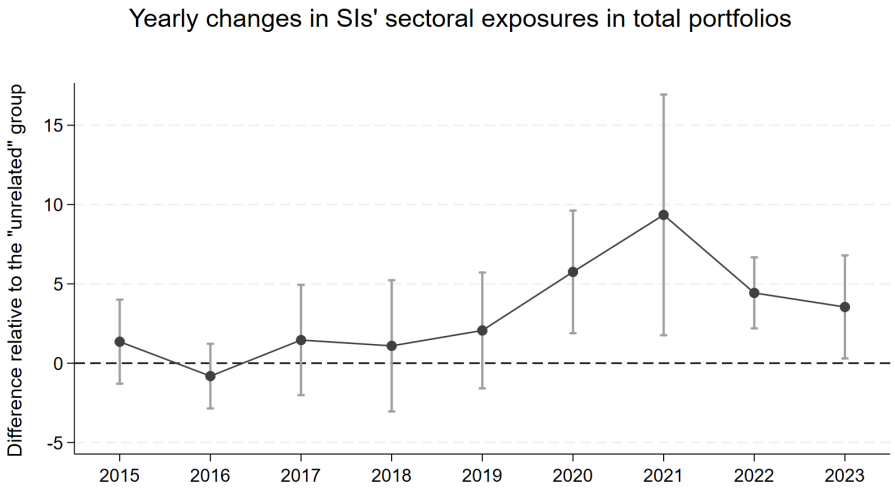


FIGURE 3. ESTIMATES WITH SIS' SECTORAL EXPOSURES OVER 2015 - 2023

This figure describes how the carbon sensitivity based on the sectoral exposures of the significant institutions (SI) 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 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 have shown an 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.

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DERIVATION AND PROOF

I first provide the derivation for the direct solution to the baseline problem 1.

The within-country price homogeneity for each type of project implies $x_k^L = x_C^L$ for all type-C projects and $x_k^L = x_D^L$ for all type-D projects provided by the foreign country, and domestically $x_h^H = x_C^H$ for all type-C projects and $x_h^H = x_D^H$ for all type-D projects. The maximization problem can be written as follows:

$$\max_{\{x_C^H, x_C^L, x_D^H, x_D^L\}} \frac{1}{(1-\frac{1}{\sigma})L}\{\pi_H n_H (d_C^H x_C^H)^{1-\frac{1}{\sigma}} + \pi_L n_L (d_C^L x_C^L)^{1-\frac{1}{\sigma}} + (1-\pi_H) n_H (d_D^H \theta_H x_D^H)^{1-\frac{1}{\sigma}} + (1-\pi_L) n_L (d_D^L \theta_H x_D^L)^{1-\frac{1}{\sigma}}\}$$

$$\text{s.t.} \quad p_H[\pi_H n_H x_C^H + (1-\pi_H) n_H x_D^H] + p_L \tau [\pi_L n_L x_C^L + (1-\pi_L) n_L x_D^L] \leq n_H y_H (1-s_H)$$

Denote the Lagrange multiplier for the budget constraint with λ_H. The FOCs with respect to x_C^H, x_C^L, x_D^H and x_D^L are given by:

$$\begin{aligned}
[x_C^H]: &\quad \frac{\pi_H n_H (d_C^H)^{1-1/\sigma} {x_C^H}^{-1/\sigma}}{L} = \lambda_H p_H \pi_H n_H \\
[x_C^L]: &\quad \frac{\pi_L n_L (d_C^L)^{1-1/\sigma} {x_C^L}^{-1/\sigma}}{L} = \lambda_H p_L \tau \pi_L n_L \\
[x_D^H]: &\quad \frac{(1-\pi_H) n_H (d_D^H \theta_H)^{1-1/\sigma} {x_D^H}^{-1/\sigma}}{L} = \lambda_H p_H (1-\pi_H) n_H \\
[x_D^L]: &\quad \frac{(1-\pi_L) n_L (d_D^L \theta_H)^{1-1/\sigma} {x_D^L}^{-1/\sigma}}{L} = \lambda_H p_L \tau (1-\pi_L) n_L
\end{aligned}$$

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

$$\begin{aligned}
x_C^H &= \frac{{d_C^H}^{\sigma-1}}{(L\lambda_H p_H)^\sigma} \;\; \& \;\; x_D^H = \frac{(d_D^H \theta_H)^{\sigma-1}}{(L\lambda_H p_H)^\sigma} \;\; \text{domestically,} \\
x_C^L &= \frac{{d_C^L}^{\sigma-1}}{(L\lambda_H p_L \tau)^\sigma} \;\; \& \;\; x_D^L = \frac{(d_D^L \theta_H)^{\sigma-1}}{(L\lambda_H p_L \tau)^\sigma} \;\; \text{abroad.}
\end{aligned}$$

By aggregating the per-project share over the available projects, I obtain the total lending values to domestic-clean (*HC*), domestic-dirty (*HD*), foreign-clean (*LC*), and foreign-dirty (*LD*) projects as shown in the Equation system 2.

I next provide the proof for propositions.

Proof (Proposition 1)**.** *Consider Country H, for example. Given that θ_H does not change π_H, R_C^H and R_D^H, the domestic carbon sensitivity of lending* $\log(\frac{X_C^H}{X_D^H}) = \log(\frac{\pi_H}{1-\pi_H}) + (\sigma-1)(\log R_C^H - {}^H_D) - (\sigma-1) log\theta_H$ *increases as θ_H (or $\log\theta_H$) decreases, because*

$$\frac{\partial(\log X_C^H - \log X_D^H)}{\partial \log \theta_H} = 1-\sigma < 0, \quad \textit{given } \sigma > 1.$$

and

$$\frac{\partial(\log X_C^H - \log X_D^H)}{\partial \theta_H} = \frac{1-\sigma}{\theta_H} < 0, \quad \textit{given } \sigma > 1 \textit{ and } 0 < \theta_H \leq 1.$$

In the same way, the foreign carbon sensitivity of lending $\log(\frac{X_C^L}{X_D^L}) = log(\frac{\pi_L}{1-\pi_L}) + (\sigma-1)(logR_C^L - logR_D^L) - (\sigma-1)log\theta_H$ *also increases as* θ_H *(or* $\log\theta_H$*) decreases.*

The same result holds between two otherwise identical countries because the only factor that causes changes in bilateral carbon sensitivity is θ_H*.*

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

$$\frac{\partial(\log X_C^H - \log X_D^H)}{\partial\theta_H} = \frac{\partial(\log X_C^L - \log X_D^L)}{\partial\theta_H} = \frac{1-\sigma}{\theta_H} < 0.$$

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

$$\begin{aligned}
&\log(\frac{X_C^H}{X_D^H}) - \log(\frac{X_C^L}{X_D^L}) \\
&= (\log(\frac{\pi_H}{1-\pi_H}) + (\sigma-1)(\log R_C^H - \log R_D^H) - (\sigma-1)\log\theta_H - (\log(\frac{\pi_L}{1-\pi_L}) + (\sigma-1)(\log R_C^L - {}^L_D) - (\sigma-1)log\theta_H) \\
&= \log\frac{\pi_H/(1-\pi_H)}{\pi_L/(1-\pi_L)} - \log\frac{R_C^H/R_D^H}{R_C^L/R_D^L}.
\end{aligned}$$

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).[38] 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 supervisor's 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 make a strong presence both within and outside the EU through policy communication and general mobilization. The use of words in ECB's publications also directly displays 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 speech on March 14, 2024, who is a member of the Executive Board of the ECB and vice-chair of the Supervisory

[38]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.



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

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.[39] Non-compliance with the

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

green expectations has been credibly inspected for SIs since 2021, whereas LSIs are followed by their national competent authorities in 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 the 2020 annual report that the 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, some other national competent authorities may still be on the way to officially incorporating the ECB's expectations into their national supervision.

All other financial institutions in the European Union receive 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 in 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 in percentage.	LPC DealScan.
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.

Table C1 continued from previous page

Variable	Description	Data Source
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 measure 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 measure 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 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 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.
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 is 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 BIS. Foreign claims are defined as the sum of cross-border claims plus foreign offices' local claims in all currencies.	World Bank.

Table C1 continued from previous page

Variable	Description	Data Source
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	ND-GAIN score is constructed by subtracting the vulnerability score from the readiness score for each country, and scale the scores to give a value 0 to 100.	Notre Dame Global Adaptation Initiative Country Index.
Self-expression Score	A value dimension created by 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
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

Table C2 continued from previous page

Country	Bilateral	Aggregate Weights	lender-loan (conditional on EIR available)	lender-year (conditional on EI available)
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
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

Table C2 continued from previous page

Country	Bilateral	Aggregate Weights	lender-loan (conditional on EIR available)	lender-year (conditional on EI available)
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 level of 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 9.

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

where l indexes (direct) lenders, K indexes sectors, and t indexes years. 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 the 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

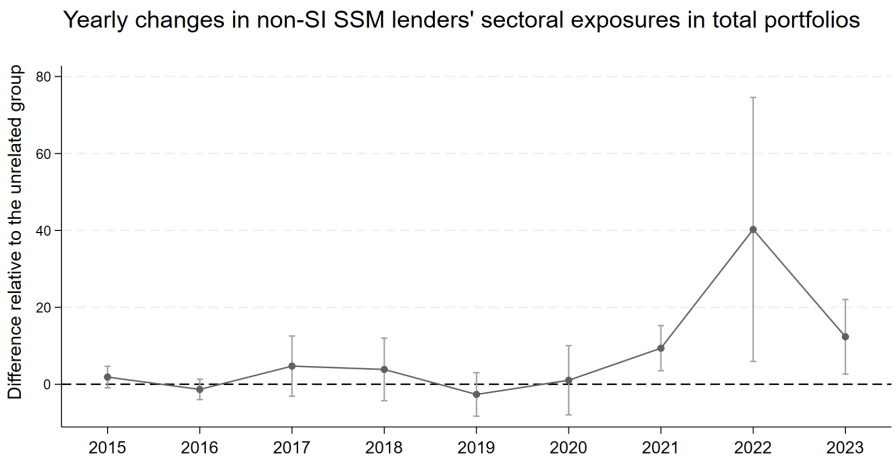


FIGURE C1. ALTERNATIVE ESTIMATES WITH SIs' SECTORAL EXPOSURES OVER 2015 - 2023

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 the "unrelated" lenders. The detailed variable definitions are in Table C1. The plotted confidence interval is at the 90% level.

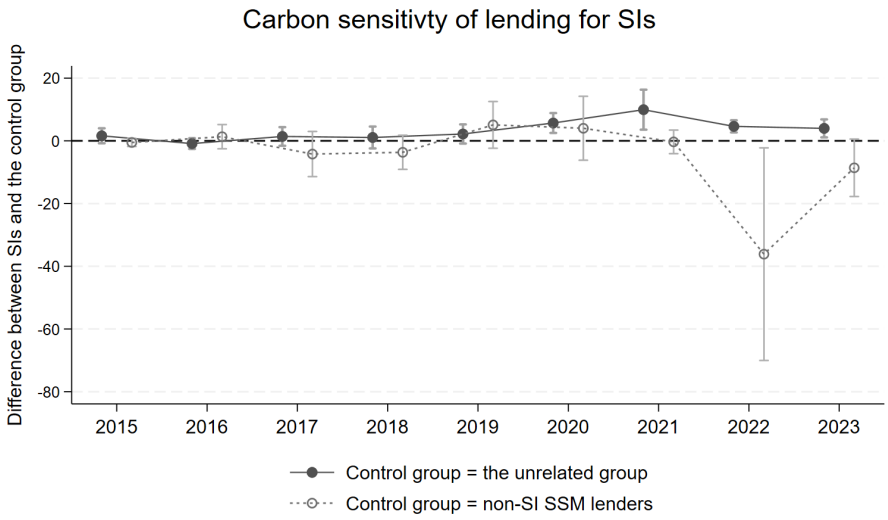


FIGURE C2. ALTERNATIVE ESTIMATES WITH SIS' SECTORAL EXPOSURES OVER 2015 - 2023

This figure plots the yearly estimates based on Equation 12 against ones based on Equation 13 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:

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

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.