"There is No Planet B", but for Banks "There are Countries B to Z": Domestic Climate Policy and Cross-Border Lending

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March 2025

Abstract

We document that banks react to domestic climate policy stringency by increasing cross-border lending. We use loan fixed effects to control for loan demand and an instrumental variable strategy to establish causality. Consistent with a race to the bottom, the positive effect increases as the borrower country becomes less stringent and is absent if the borrower country is more stringent. Furthermore, climate policy stringency decreases loan supply to domestic borrowers with high carbon risk while increasing loan supply to high-risk borrowers abroad. Our results suggest that cross-border lending enables lenders to exploit the lack of global coordination in climate policies.

JEL classification: G21, H73, Q58.

Keywords: Cross-border lending, climate policy, race to the bottom.

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The authors would like to thank Daron Acemoglu, Marco Ceccarelli, Matthieu Chavaz, Ralph De Haas, Mintra Dwarkasing, Max Daniel Eilert, Michael Gelman, Alberto Manconi, Panagiota Makrychoriti, Yingjie Qi, Kasper Roszbach, Glenn Schepens, Rik Sen, Johannes Stroebel, Misa Tanaka, Alan M. Taylor, Brigitte Roth Tran, Annette Vissing-Jorgensen, Sumudu Watugala, Daniel Wilson as well as participants at the Banca d'Italia Workshop on Climate Risks, BOFIT Workshop, CAFRAL, Croatian Central Bank, ECB Banking Supervision Research Conference, FRBSF Climate Risks Workshop, GRASFI, NEOMA Sustainable Finance Conference, Norges Bank, SFI Research Days, SFS NA Cavalcade, SGF Conference, Western Finance Association Conference, Workshop on Environmental Finance for the Common Good at Birkbeck College, seminars at Audencia Business School, Bangor Business School, Bundesbank, ESSEC, Montpellier Business School, NTNU Business School, Reserve Bank of Australia, Universities of Edinburgh, Liverpool, Luxembourg, Manchester, Naples Federico II, New South Wales, Sydney Business School, Technology Sydney, and Zurich for helpful suggestions and comments.

1 Introduction

Climate change is a global problem whose solution needs global coordination and cooperation.[1] Despite this need, there exists a significant heterogeneity in climate policy stringency across countries, which may lead to numerous consequences. For example, banks may respond to the heterogeneous stringency in countries' climate policies by turning to international markets to increase their lending across borders. In this context, however, the effect could be ambiguous. On the one hand, stricter climate policies may increase firms' loan demand as the transition into a low-carbon economy requires investment, and banks may reduce their cross-border lending to satisfy the higher loan demand at home. On the other hand, these policies may make lending to domestic firms less appealing due to the transition risks –risks stemming from incumbent climate regulations– and affect banks' loan portfolios adversely. Therefore, banks may increase their cross-border lending to reduce their exposure to stringent climate policies. While the former suggests a negative financial spillover, the latter suggests a race to the bottom behavior by banks, which can undermine the efforts to transition to low-carbon economies.

In this paper, we consider both of these channels and empirically investigate whether and how banks increase cross-border lending as a response to strict climate policies in their home country. To this aim, we use a sample of syndicated loans for the years between 2007 and 2017, where banks are located in 39 different countries, and borrowers are located in 40 different countries. We combine syndicated loans with a global index on climate policy stringency and find that banks react to strict climate policy in their home country by increasing their cross-border lending. To put the magnitude of the effect in perspective, we can consider a hypothetical example of a cross-border syndicated loan where one bank is located in the UK, the other bank is in Australia, and the borrower is in a third country, say, Brazil. Our results indicate that the UK's 35 index points more stringent climate policy in 2015 leads the bank in the UK to have a 19.25 percent higher loan share in this loan compared to the bank located in Australia. Saturating our models with loan fixed effects, we show that the increase in cross-border lending is not driven by the borrower's demand for bank credit. Moreover, we dispel concerns about omitted variables by instrumenting climate policy stringency with the time since the country's economy crossed the industrialization path.

Our measure of climate policy stringency is the Climate Change Performance Index

[1] In the January 27th, 2021, "Executive Order on Tackling the Climate Crisis at Home and Abroad" by U.S. President Biden, it is stressed that "domestic action must go hand in hand with United States international leadership, aimed at significantly enhancing global action (link)."

(CCPI).[2] As a popular index among academicians and practitioners, CCPI has three main advantages. First, countries use different policies against climate change with different intensities, making a cross-country comparison an empirical challenge. CCPI overcomes this challenge by utilizing climate policy experts to aggregate all different climate policies into one metric. Second, CCPI has extensive coverage across countries and time, enabling us to study a large portion of the universe of cross-border lending. Third, by consisting of both climate policies and the outcome of these policies, such as emission reduction improvements and efficiency in energy usage, CCPI measures policy stringency more accurately and is less prone to greenwashing. We combine CCPI with syndicated loans, which we use to assess cross-border bank lending. Syndicated loans are one of the main tools for cross-border lending (De Haas and Van Horen, 2013). In addition, syndicated loans make cross-border lending easier for smaller banks, as the lead arranger of a syndicated loan can take actions to reduce the information asymmetries (Sufi, 2007). Therefore, the combination of a unique metric, such as the CCPI, and syndicated loans provides an ideal setting to investigate whether banks alter their cross-border lending as a response to climate policy stringency in their home country.

A naive regression model that estimates a positive coefficient for climate policy stringency on cross-border lending can suffer from two primary sources of endogeneity. The first one is about loan demand. After observing an increase in a country's climate policy stringency, a borrower may increase its loan demand to the banks from that country. Such increased demand may be strategically driven by the borrower's decision to use the relationship with a bank from a stringent country as a signaling device. Alternatively, the borrower may want to improve its knowledge in efforts against climate change, and a lending relationship with this bank can provide this knowledge. These arguments imply that the borrower's loan demand can be lender-country-specific, which violates the Khwaja-Mian estimator's main assumption that loan demand is constant across the lenders of a borrower over time (Khwaja and Mian, 2008).

We tackle this challenge by using loan fixed effects to control for loan demand. Loan fixed effects provide an exemplary approach to control for loan demand in a syndicated loan sample, thanks to the institutional setting of syndicated loans. Typically, there are multiple banks in a single syndicated loan; one of them is called the lead arranger and performs the main banking tasks, and the others are called participants. The participant banks join the syndicated loan after the loan terms, such as loan amount and interest rate, are determined. Moreover, these participants have limited interactions with the borrower such that their loan

[2]CCPI is developed by Germanwatch with the aim to track efforts to combat climate change (Burck et al., 2016). We provide more details on CCPI in Section 2.

supply decisions are made after both the credit demand and the loan terms are settled. This implies that their loan supply is not affected by the loan demand due to a lack of interaction with the borrower. Therefore, the within-loan comparison, which is more granular than the standard within-borrower-time comparison, allows us to identify the loan supply effects of climate policy stringency.

The second concern is about the variables that are correlated with both policy stringency and cross-border lending. An improvement in economic conditions, for instance, can lead to an increase in policy stringency and cross-border loan supply. Or, a change in the demographics of the country can affect policy stringency by altering the perception of climate change and cross-border lending by affecting loan demand. We show that controlling for a rich set of factors that are found to be related to cross-border lending in the literature or comparing banks from countries that are in the same regional area, such as Norway and Sweden, in the same year does not change the positive effect of climate policy stringency on cross-border lending. Nonethless, unobservable variables can still induce omitted variable bias, which we tackle with the following exercises.

In the first exercise, we exploit the difference in policy stringency between the lender and borrower country. The main idea of this exercise is that the difference between the lender and borrower country gives two specific implications that are not likely to be driven by an omitted variable. Thus, confirming these implications in our setting would suggest that the main driver of the results is climate policy stringency. The first implication is that if banks use cross-border lending to decrease their exposure to climate policies, the banks should not increase their cross-border lending if the borrower country has a climate policy that is stricter than the home country one. Second, banks should increase their cross-border lending more as the borrower country's stringency decreases. We provide evidence in favor of these implications, thereby confirming that the increase in cross-border lending is solely driven by the strict home country climate policy.

In the second exercise, we exploit the environmental Kuznets curve and use the time since a country's income level becomes above a threshold as an instrument for climate policy stringency. The environmental Kuznets curve states that while a country's environmental performance worsens as the country becomes more industrialized, after an inflection point, this relationship reverses, and the country's environmental performance improves with its economic development (Grossman and Krueger, 1995). Thus, the environmental Kuznets curve indicates that a country should have more stringent climate policies if it is located further along this curve. Building on this vast literature, we use the time since the country's real GDP per capita in 2011 USD terms has reached USD 5,000 as the inflection point. In line with the environmental Kuznets curve, we find a strong first stage and again estimate a positive effect on cross-border lending with the instrumented policy stringency. In addition to climate policies, the time since industrialization may affect economic conditions that influence cross-border lending, creating a threat for the exclusion restriction condition. To mitigate related concerns, we control for several proxies of economic conditions in our models. Furthermore, we relax the exact exclusion restriction with the method developed by Conley et al. (2012), a method that demonstrates that the magnitude of the effect of the time since industrialization through other channels should be as large as the size of its effect through climate policy stringency to make the latter insignificant. We find this implausible, considering that we already control for the most probable alternative channels.

After establishing the positive effect of climate policy stringency on cross-border lending, we investigate the underlying mechanism. Our findings indicate that banks use cross-border lending as a tool for the race to the bottom. Race to the bottom refers to banks' actions to reduce the influence of changes in regulations on their loan portfolios (Acharya et al., 2009; Houston et al., 2012). In our context, a stringent climate policy can induce a reallocation of resources that may deteriorate the business conditions and profitability of some firms. As these firms can be banks' borrowers, the climate policy may adversely affect their loan portfolios and incentivize them to increase their cross-border lending—a race to the bottom behavior. Indeed, we show that as climate policies become more stringent, banks' loan portfolio performance worsens, measured by the non-performing loans (NPL) ratio and return on assets. In line with worse performance, banks charge higher spreads in domestic syndicated loans, indicative of a lower domestic loan supply. These results explain why banks perform race to the bottom behavior by increasing their cross-border lending to less stringent countries.

The race to the bottom in the context of climate policy has specific predictions for lending to borrowers with high carbon risks or polluting businesses. Namely, higher climate policy stringency may hinder lending to domestic borrowers with high carbon risk, encouraging banks to increase their cross-border lending to foreign borrowers with high carbon risk. We collect borrower-level carbon risk intensity information and include domestic lending in our data set to test these two hypotheses together. We find that climate policy stringency reduces domestic lending to borrowers with high carbon risk, while it increases cross-border lending to borrowers with high carbon risk. These results suggest a lending reallocation that points to a race to the bottom mechanism.

We support our findings for the underlying mechanism with three additional exercises. The first exercise considers bank specialization in domestic markets. Race to the bottom behavior suggests that banks should utilize their sectoral expertise at home to reduce monitoring and screening costs while granting a cross-border loan. We find that the effect is stronger for loans that are banks specialized in their domestic markets. Second, this type of lending may provoke negative publicity and hurt the bank's reputation, suggesting that banks should increase their cross-border lending where their reputation is less at stake. We find that the effect is larger when the bank's reputation is less likely to be affected. Last, race to the bottom behavior can also attract the attention of the supervisory authority with possible penalties. In line with this intuition, the effect is smaller if the domestic country's bank supervisory authority is more powerful. We also investigate the role of domestic borrowers in the mechanism. By moving their activities to their foreign subsidiaries, domestic borrowers can incentivize banks to pursue a race to the bottom behavior. Even though banks are more likely to extend loans to foreign subsidiaries of their domestic borrowers, the effect is too small and becomes insignificant when controls are added.

Next, we exploit the heterogeneity among the banks and borrowers. Exercises on bank-level heterogeneity show that banks that are more expected to engage with cross-border lending as a reaction to climate policy stringency are indeed the ones who are more likely to do so. For instance, the magnitude of the effect is significantly larger for the banks that have higher cross-border loans in their books and for banks that face a higher nonperforming loans ratio. A higher cross-border loan ratio implies that the banks have more experience with cross-border lending, which means it is easier for this bank to cater to the international syndicated loan market as a response to the domestic climate policy stringency. Moreover, a higher NPL ratio creates a stronger incentive for the bank to increase lending abroad since a more stringent climate policy can reduce the returns of the loans when the bank needs a higher return rate due to the high NPL ratio. Regarding geographical heterogeneity among borrowers, we focus on European lenders and find that European banks increase their cross-border lending more to borrowers in emerging market countries. At the same time, the effect is insignificant if the borrowers and banks are located in Europe.

Last, we assess the sensitivity of our results to different metrics of climate policy stringency and cross-border lending. First, we tackle the concern that our results might be driven by the CCPI measure itself. Even though CCPI fits our research question very well, the way it is constructed could play a role in our findings, limiting the external validity of our results. Therefore, we use three other commonly used climate policy stringency indices—Climate Change Cooperation Index, OECD's Environmental Policy Stringency Index, and the Environmental Performance Index, and find the same results, thus alleviating the related concerns. Then, we use loan amounts instead of loan shares as the dependent variable in loan-level regressions. If loan amounts decrease as climate policy becomes stricter, higher lender shares can mask the decline in loan amounts. Yet, we find identical results when the loan amount is the dependent variable. Finally, we aggregate the loan level data up to the borrower country level and use the number and volume of loans between the banks and the borrowing country as dependent variables. Although the loan-level data improves identification, it can mask the aggregate changes, such as the number of cross-border loans from a bank to a country decreasing with policy stringency. The results are confirmed when replicating our main finding with borrower country-level data.

Our paper mainly contributes to the literature on climate change and finance. First, our paper is related to the discussions about the challenges that the financial markets entail regarding the transition to a green economy. One such challenge is created by the policies implemented to fight against climate change, known as the regulatory risk (Krueger et al., 2020; Seltzer et al., 2020; Ilhan et al., 2021; Stroebel and Wurgler, 2021).[3] Due to this challenge, firms may prefer to reallocate their activities to the areas with less stringent climate policies (Bartram et al., 2022).[4] Close to our work, Ben-David et al. (2021) document that multinational firms that are headquartered in countries with stringent climate policies are more likely to execute their polluting activities in countries with less stringent policies. We add to their work by showing that banks use cross-border lending as a tool to protect their loan portfolio's exposure to climate policies. Specifically, we show that banks increase lending to borrowers in countries with less stringent countries as a response to an increase in their home countries' climate policy stringency. This finding indicates that banks exploit the lack of homogeneity in climate policy stringency across countries through a cross-border lending channel, decreasing the effectiveness of such policies.

Second, our paper is also related to literature about the role of banks in the fight against climate change. While banks provide less demanding funding sources to browner firms compared to the bonds and stocks market (De Haas and Popov, 2023; Beyene et al., 2024), they reflect the climate risk on loan terms (Atanasova and Schwartz, 2019; Correa et al., 2022; Bolton and Kacperczyk, 2021; Delis et al., 2024; Mueller and Sfrappini, 2022; Ivanov et al., 2024). In addition, banks lower their loan supply to browner firms after committing themselves to carbon neutrality (Kacperczyk and Peydro, 2021).[5] We complement these

[3] In addition to regulatory risks, climate change creates physical risks through extreme weather events (Kruttli et al., 2021) and sea-level rise (Bernstein et al., 2019; Baldauf et al., 2020; Bakkensen and Barrage, 2022). Investors may demand higher returns considering these risks (Chava, 2014; Painter, 2020; Bolton and Kacperczyk, 2021; Hsu et al., 2023; Nguyen et al., 2022).

[4] Bartram et al. (2022) show that financially constrained firms shift their production to the outside of California after California's cap-and-trade program. See also Li and Zhou (2017); Dai et al. (2021).

[5] Degryse et al. (2023) show that environmentally conscious banks offer cheaper loans to green firms after the Paris Agreement.

findings by studying how banks adjust their domestic and cross-border lending according to their home country's climate policy stringency. After an increase in their home country's policy stringency, we document that banks decrease their domestic loan supply to browner firms while increasing cross-border lending to browner firms abroad.

Finally, we add to the strand of literature that examines cross-border lending incentives. Cross-border lending can be an important tool to transmit shocks among countries (Cetorelli and Goldberg, 2011; Giannetti and Laeven, 2012; Ongena et al., 2015; Claessens, 2017; Hale et al., 2020). So far, the literature has established that geographical and cultural proximity (Mian, 2006; Lin et al., 2012), bank acquisitions and capital requirements (Karolyi and Taboada, 2015; Gao and Jang, 2021), and regulatory arbitrage opportunities (Houston et al., 2012; Ongena et al., 2013; Demyanyk and Loutskina, 2016; Beck et al., 2024) are drivers of cross-border lending. Linking to existing work that examines the influence of international differences in corporate taxes on firm behavior (Bartelsman and Beetsma, 2003; Huizinga et al., 2008; Dischinger and Riedel, 2011), Laeven and Popov (2023) show that the incidence of carbon taxes can influence the reallocation of fossil lending across the borders. Our paper complements the existing literature on cross-border lending in three ways. First, we document that heterogeneity in country-level climate policy stringency that accounts for all climate-related policies and their outcomes can also induce cross-border lending by incentivizing banks to engage in a race to the bottom behavior. Second, we introduce loan fixed effects as a tool to control for loan demand, which is particularly important in a cross-border lending setting since borrowers' loan demand can be lender-country-specific—this specificity violates the main Khwaja-Mian estimator assumption of loan demand being constant across lenders. Third, we show that the climate policy-induced increase in cross-border lending decreases as the domestic banking regulator strengthens. This suggests that strong banking regulation may complement climate policies by preventing banks from creating shortcuts for such policies.

The rest of the paper is organized as follows: Section 2 describes the data and variables, Section 3 discusses the empirical strategy, Section 4 reports the results, and Section 5 concludes.

2 Data

Our analysis combines several data sources to assess climate policy stringency and estimate its effects on cross-border lending. This section describes the main variables and how we construct the sample. Appendix A provides additional details on the data and discusses the remaining variables. Table A1 provides the variables' description.

Climate policy stringency Our measure of climate policy stringency is the Climate Change Performance Index (CCPI), whose main aim is to allow countries to compare their climate protection progress (Burck et al., 2016). This annual index is developed by Germanwatch—a non-profit organization, and is published in collaboration with the NewClimate Institute and the Climate Action Network. CCPI consists of four main components: GHG Emissions Improvement (60%), Renewable Energy (10%), Energy Efficiency (10%), and Climate Policy (20%), where its range is between 0 and 100 and higher scores indicating better performance. CCPI gives weights to both levels and changes in levels of these components to be able to reflect both current conditions and recent developments in the country.[6] By being available for 59 countries, CCPI covers almost 90 percent of global GHG emissions, making it one of the most extensive indices for climate policies. Due to a change in methodology in the CCPI and external shocks such as COVID-19, our sample period ends in 2017.[7]

We use CCPI as our climate policy stringency measure thanks to its several advantages. Countries have various policies regarding climate change, reflecting their different approaches. This nature of climate policies makes cross-country comparisons a significant challenge. For instance, focusing only on one policy would mean overlooking other policies, leading to a severe mismeasurement problem. Also, different policies have different implications for the efforts regarding the fight against climate change, meaning that a cross-country comparison would entail a careful aggregation of various climate policies. In addition, even if countries have the same policies, they may implement the same policies with different intensities. CCPI rigorously tackles all of these challenges. Namely, around 450 independent climate experts carefully evaluate all aspects of the countries' climate policies each year. These evaluations consider different intensities of the same policy and incorporate different policies into a single framework. Therefore, CCPI enables us to compare countries with a single variable.

CCPI's next advantage is thanks to how it is constructed. Like other policies, the effectiveness of climate policies depends on whether their intended outcomes align with the realized outcomes. If the policymakers do not implement the policy with the needed intensity, there could be a difference between the intended and realized outcomes, meaning the

[6]The main reason for giving weights to both levels and changes in levels is to make the countries in different phases of economic development more comparable. For instance, on average, advanced countries emit more GHG per capita and contribute to climate change more, while developing countries emit less. At the same time, the recent developments in advanced countries demonstrate a more positive picture than the developing countries. By considering both levels and changes in levels, CCPI aims to provide a fair and thorough assessment.

[7]Our results do not change when we extend our sample to 2023 as shown in Table A9.

policy itself may not reflect its stringency correctly. This could be a specifically important problem for climate policies due to the vagueness of their nature and possibilities for greenwashing. Therefore, to measure the policy effectiveness correctly, CCPI considers both the policies and their outcomes by giving weight to policy outcomes, such as GHG emissions. Moreover, CCPI uses only the emissions generated by domestic production (not consumption), making CCPI a particularly good fit for our research question as we are interested in banks' reactions to changes in firms' behavior induced by climate policies. Moreover, being a transparent index, using CCPI limits the researcher's discretionary power and subjective choices. Thanks to these advantages, CCPI is heavily used by researchers (e.g., Atanasova and Schwartz (2019); Bolton and Kacperczyk (2023)), the financial industry (e.g., Blackrock, NN Investment), and policy institutions (e.g., World Bank, Financial Stability Board).[8]

Figure A1 plots the average CCPI against its standard deviation for all countries included in our sample. European countries typically have more stringent climate policies than emerging economies, Anglo-Saxon, and Asian countries. As expected, Scandinavian countries stand out in their climate performance.[9] Panel A of Figure A2 depicts the change in the climate policy stringency over time. This figure shows a general improvement in climate policy stringency, which varies, however, across the sample countries. Panel B of Figure A2 plots instead the percentage change in the CCPI over time, showing a clear time-variation among countries' climate policy stringency.

Bank loans and balance sheets We follow the literature and use syndicated loans to measure cross-border lending (e.g., Giannetti and Laeven (2012); Ferreira and Matos (2012); De Haas and Van Horen (2013); Ivashina et al. (2015); Gao and Jang (2021)). Specifically, we use the syndicated loans originated between 2007 and 2017 by commercial, savings, cooperative, and investment banks to non-financial firms (excluding SIC codes between 6000 and 6999). Data comes from the LPC DealScan database and contains information about the loan amount, maturity, origination, borrowers, and lenders. The dependent variable of our analysis is *lender share*, which is the share of a lender in a cross-border syndicated loan. We define a loan as cross-border on a locational basis, thereby the lender and borrower are located in different countries (De Haas and Van Horen, 2013).[10] We use only reported loan

[8]See Appendix Section A for details on the importance of the CCPI for practitioners and financial actors.

[9]Details about the countries included in our sample and their average CCPI values are reported in Appendix Figure A3, while details about the variation in the CCPI's components are depicted in Appendix Figure A4.

[10]Even though the lenders may sell their shares, the secondary market of the syndicated loans is active mostly only for the American market. Thus, lenders are likely to keep the cross-border loan shares in their books. In line with this, Tamura and Tabakis (2013) report that the secondary market in Europe is significantly smaller than the one in the USA.

shares without imputing for the missing observations.[11] In Table 1, we report the summary statistics. Our final sample comprises 11,671 cross-border loan shares.[12] In our sample, the average value of loan shares is 7.6 percent, with a standard deviation of 7.66. Almost half of the syndicates are collateralized. A syndicated loan has 6 participants on average and an average maturity of 51 months. We collect bank balance sheet data from Bankscope and BankFocus. We have 376 banks (of which 294 are parent banks) located in 39 countries in our cross-border sample. We match the bank-level data to climate policy stringency using the country of each bank. We use the banks' headquarters locations to determine the banks' countries. If a bank is a subsidiary of another bank located in another country, we use the country of the subsidiary as the bank's country. We identify firms' locations by using the headquarters country information in Compustat. Our sample includes a total of 1,146 firms located in 40 countries.

3 Empirical strategy

Our objective is to estimate the causal effect of the home country's climate policy stringency on cross-border lending. To this end, we need to address two main identification challenges. The first one is about loan demand. A country's climate policy stringency can alter the loan demand to the banks of that country from abroad. The second challenge is that an omitted variable can affect both climate policy stringency and cross-border lending. These two challenges suggest that our empirical strategy needs to control for loan demand properly and have an exogenous variation in climate policy stringency.

We tackle these two challenges in two steps. In the first step, we exploit the granularity of our data to control for loan demand. Controlling for loan demand is essential to estimate the causal relationship in our setting since climate policy could be correlated with the loan demand of foreign borrowers. For instance, firms could consider a lending relationship with a bank in a stringent country as a positive signaling device, suggesting that a stricter climate policy could attract loan demand from abroad. Alternatively, if firms anticipate that banks are willing to increase their cross-border lending as a reaction to a more stringent climate policy, they would increase their loan demand to such banks.

To control for loan demand, we saturate our model with loan fixed effects. Using granular

[11] This is available for 28 percent of the sample in the period 2007-2017. Imputing the missing loan shares does not change our baseline results (see Section 4.4). We also remove observations with incorrect values, such as total loan shares larger than 100 or loan shares equal to 0.

[12] 45 percent of the syndicated loan shares are cross-border shares between 2007 and 2017. Approximately 23 percent of these shares have non-missing loan share information, yielding 11,671 cross-border loan shares.

Table 1: **Summary statistics**

This table provides the summary statistics of our sample. The sample consists of cross-border loan shares in the syndicated loan market. Balance sheet variables are at an annual frequency. For variable definitions, see Table A1.

	Obs.	Mean	Std. Dev.	Minimum	Maximum
Lender share	11,671	7.595	7.664	0.070	94.210
$CCPI_{lender}$	11,671	56.090	8.057	22.848	76.620
$CCPI_{borrower}$	11,671	50.095	9.070	22.848	76.620
Bank-level controls					
log(Total assets)	11,671	28.055	3.072	11.169	36.838
Tier 1 capital ratio	11,671	12.327	7.723	3.700	182.760
log(Customer deposits)	11,671	27.196	3.338	11.727	36.813
Liquidity ratio	11,671	49.885	36.666	0.720	395.494
ROAE	11,671	5.540	11.583	-223.690	46.090
Net interest margin	11,671	1.473	0.779	-0.130	9.170
Country-level controls					
log(GDP per capita)	11,157	10.481	0.718	6.906	11.685
GDP growth	11,157	1.934	2.653	-8.075	14.526
Domestic credit to GDP	10,944	118.850	36.422	25.456	206.671
Unemployment rate	11,157	7.646	3.535	0.489	27.071
Common Language	10,670	0.240	0.427	0	1
log(Distance)	10,670	7.885	1.038	4.798	9.384
Top 5 bank concentration	11,464	74.543	13.916	35.495	100
Population growth	11,158	0.530	0.529	-1.854	5.322
Young workforce	11,157	26.405	4.4	15.767	55.337
Old workforce	11,157	25.625	6.343	4.192	45.125
Capital regulatory index	8,315	6.782	1.798	3	10
Independence of supervisory authority	9,922	2.012	0.831	0	3
Property rights	11,062	76.786	18.748	20	97.100
log(Contract enforcing days)	6,161	4.607	0.504	3.258	5.720
Climate $policy_{lender}$	11,671	12.223	4.180	0	20
Renewable $energy_{lender}$	11,671	2.636	1.719	0.023	8.094
Energy $efficiency_{lender}$	11,671	5.749	1.439	1.017	9.124
$CO_{2lender}$	11,671	35.481	5.286	9.570	45.564
Loan characteristics					
Number of lenders	11,671	5.587	3.465	2	26
log(Loan amount)	11,671	17.374	1.534	7.427	21.563
Loan spread	8,915	171.998	109.575	2	1150
Others					
log(Years since GDP_{pc}>5k)	10,993	4.495	0.775	0	5.989
High Carbon Intensity Risk	1,385	0.723	0.448	0	1
Bank Supervisory Power	10,482	9.958	1.816	6	16
Ind. of Bank Supervisory Auth.	9,971	2.012	0.832	0	3
$C3\text{-}I_{lender}$	2,441	54.672	1.865	48.455	58.345
EPI_{lender}	10,790	83.068	7.248	53.580	91.050
EPS_{lender}	11,052	3.231	0.692	0.167	4.222

fixed effects has become the standard way of controlling for loan demand. The main assumption of this practice is that a firm's loan demand is homogeneous across its banks at the granularity of the fixed effects (Khwaja and Mian, 2008). For instance, when *borrower* × *year* fixed effects is used, the assumption is that the borrower's loan demand is constant across its lenders at the same year. Yet, this assumption is less likely to hold in a cross-border lending setting since the borrower's loan demand could be lender-country-specific, as explained above. At the same time, the loan fixed effects in a syndicated loan setting provide an exemplary implementation as this assumption is likely to be satisfied thanks to the institutional details of the syndicated loans. Typically, in a syndicated loan, the lead arranger is the one who negotiates the loan amount and other terms with the borrower. After the lead arranger and the borrower agree on these terms, the lead arranger invites other lenders to participate in the syndicated loan, which means that the participants join the syndicated loan after the effect of loan demand on equilibrium loan outcomes is completed (Dennis and Mullineaux, 2000; Sufi, 2007; Ivashina, 2009). Moreover, the limited interaction between the participants and the borrower indicates that the borrower cannot influence the decisions of the participant banks. For instance, the borrower cannot influence which banks would participate in the loan, effectively preventing any borrower-lender selection effect from influencing the estimations.[13] Thanks to these features, the participants' loan supply decisions, indicated by their loan shares, are not affected by the loan demand. This suggests that comparing these shares in the same loan is possibly the cleanest way to keep the loan demand constant.[14] To make a within-loan comparison, we include loan fixed effects (α_l) in our preferred specification and estimate the following model:

$$\text{Lender Share}_{\text{blft}} = \alpha_{\text{l}} + \beta \text{CCPI}_{\text{ct}} + \gamma \mathbf{X}_{\text{bt-1}} + \varepsilon_{\text{blft}} \tag{1}$$

where $\text{Lender Share}_{\text{blft}}$ is the cross-border loan share that bank b finances in loan l to firm f in year t.[15] The variable of interest is CCPI_{ct}, which measures the climate policy stringency of the country where the bank is located (hereafter lender-country) and is indexed by c. As explained in Section 2, CCPI_{ct} reflects the recent changes in levels in its subcategories directly, meaning that β captures these changes without any need for adjustments.[16] Moreover, thanks to the loan fixed effects, β provides an interpretation in relative terms across the banks holding the borrower and loan factors, such as loan demand and borrower climate policy stringency, constant.[17] $\mathbf{X}_{\text{blt-1}}$ includes lagged bank-level controls such as bank size (log of total assets), bank capital ratio (Tier 1 capital ratio), bank performance and financial health (ROE, Net interest margin, log of customer deposits) and bank's liquid assets position (liquidity ratio). We cluster the standard errors at the lender's country-year

[13]Loan demand can influence the participant selection if the borrower targets a lead arranger due to its domestic climate policy and the lead arranger picks participants from its local network. We address this concern in Table A2 by removing participants from the lead arranger's country in a robustness check.

[14]As loan fixed effects require multiple lenders to be in a loan, loans with a single lender are dropped. Yet, such loans are only 15 percent of the sample.

[15]In Section 4.4, we show that our results do not change when we use loan amounts as the dependent variable or aggregate our sample at the bank-borrower country and use the number and volume of loans at the bank-borrower country level as dependent variables.

[16]This feature indicates that the change in CCPI between two time periods would mean taking a double difference. Moreover, we also check whether CCPI exhibits a time trend and fail to find any evidence for such a trend. This is expected since CCPI is bounded by 0 and 100.

[17]For instance, using the difference between $\text{CCPI}_{\text{lender}}$ and $\text{CCPI}_{\text{borrower}}$ yields exactly same coefficients since loan fixed effects capture all variation at the borrower-year level.

level as it is the unit of treatment (Abadie et al., 2022).[18]

In the second step, we address the challenge created by the variables that can be correlated with both climate policy stringency and cross-border lending. So far, the literature has documented that laws and institutions (Qian and Strahan, 2007; Houston et al., 2012; Ongena et al., 2013), cultural and geographical proximity (Mian, 2006; Giannetti and Yafeh, 2012), economic conditions and demographics (Giannetti and Laeven, 2012; Hale et al., 2020) affect cross-border lending. We start the second step by documenting that including these variables as controls does not change our results. Next, we exploit the difference between climate policy stringency between the lender and borrower country. The difference between the lender and borrower countries provides specific predictions that omitted variables are not likely to generate: the effect should be nonexistent when the borrower country has a higher stringency, and the effect should increase as the borrower country becomes less stringent. We test and confirm these two predictions in our setting.

Lastly, we use an instrumental variable strategy to have an exogenous variation in policy stringency. Specifically, we employ the environmental Kuznets curve concept and use the time a country's income level crosses a threshold as an instrument for climate policy stringency (Grossman and Krueger, 1995). The main idea of the environmental Kuznets curve is that economic development and a country's environmental performance have a U-shaped relationship. At lower economic development levels, a country's environmental performance deteriorates as the country becomes more industrialized. The reasons behind this empirical pattern are that people value their income more than the environment, clean production is relatively too expensive, and the regulations are either weak or not implemented. However, as the country has become more industrialized, it reaches an inflection point, and its environmental performance improves with economic development. This change is driven by changes in industrial composition, technological advances that the country experiences, and the shift in society's perception of environmental problems. In particular, as the country moves along this curve, the society attains higher environmental awareness and demands stricter climate regulations (Dinda, 2004). Therefore, the environmental Kuznets curve suggests that the further a country's location on the curve, the more stringent its climate policies should be, allowing us to have the relevance condition to be satisfied. We follow the literature and measure a country's location on the curve by the logarithm of the time in years since a country's GDP per capita exceeds USD 5,000, which we refer to as the time since industrialization (Dasgupta et al., 2002).[19]

[18] The inference does not change when we cluster the standard errors at the lender's country level.

[19] Our data comes from the Maddison Project Database 2020 (Bolt and van Zanden, 2025), which provides information on comparative income levels over the very long run since the 1800s. We use real GDP per capita

In addition to the relevance condition, the country's time since industrialization should satisfy the exclusion restriction. In our context, exclusion restriction means that the time since industrialization should not affect cross-border lending other than its effect through the climate policy stringency. This assumption would be violated if, for instance, time since industrialization affects both the climate policy stringency and economic conditions, as changes in these variables are likely to affect cross-border lending. As it is likely that economic conditions are likely to be affected by the time since industrialization, we control for economic condition variables, such as current levels of GDP per capita, GDP growth, unemployment rate, domestic credit to GDP ratio, trade openness, and exchange rate changes.[20] Thus, the variation that we exploit is clean from such factors and arguably in line with the exclusion restriction condition. Moreover, we assess how much the exclusion restriction should be violated to make our results insignificant with the method developed by Conley et al. (2012) in a robustness check in Section 4.

4 Results

In this section, we use syndicated loans to measure cross-border lending and the CCPI to measure climate policy stringency to study whether banks use cross-border lending to react to the climate policy stringency in their home country. In Section 4.1, we give the main results, in which we use granular fixed effects to control for loan demand, a rich set of control variables, the difference in policy stringency between the lender and the borrower country, and an instrumental variable strategy to mitigate concerns related to omitted variable bias. In Section 4.2, we provide our findings regarding the underlying mechanism. In Section 4.3, we describe additional analysis exploiting the heterogeneity in bank and regional characteristics in our sample, along with different available climate policy measures. Finally, Section 4.4 concludes with a battery of robustness tests to determine the sensitivity of our results.

Before moving to the regression models, Figure A5 plots a strong and positive correlation between the policy stringency and cross-border loan share on the bank balance sheets. Even though this plot suggests that banks may use cross-border lending to react to higher climate policy stringency, this positive correlation can be driven by other factors, such as loan demand and variables correlated with both policy stringency and loan supply. We use the regression models to document that this positive correlation is indeed driven by banks' reaction to the

in 2011 USD terms to construct our instrumental variable. Our results do not change when we use different cutoff values such as USD 8,000. The only lender country that has a GDP per capita lower than USD 5,000 is India. This means we lose around 1 percent of our observations in the IV estimations.

[20]Trade openness is defined as the ratio of (imports+exports)/GDP.

climate policy stringency in their home countries.

4.1 Main results

We start our regression analysis with the model in Equation 1, in which we regress Lender Share in syndicated loans on the climate policy stringency of the bank's home country. As mentioned in Section 3, one of the concerns with this model is that loan demand can be correlated with policy stringency. For instance, observing an increase in policy stringency of a country, the borrower may decide to increase its demand to the lenders from that country. The reason might be that having a lending relationship with a lender from a stringent country can generate a positive signal for the borrower. Alternatively, the borrower might want to increase its compliance with climate policies, and a lending relationship with a lender from a stringent country can facilitate this process.

To mitigate the concerns related to loan demand, we use granular fixed effects to control for borrower characteristics and report the results in Table 2. Column (1) starts with lender-level control variables, such as log(total assets), capital ratio, and liquidity ratio. We include borrower- and year-fixed effects in columns (2) and (3). In column (4), we saturate the model with borrower×year fixed effects, which means we compare loan shares of different lenders for the same borrower in the same year.

Table 2: **Effect of home country climate policy stringency on cross-border lending**

This table reports estimates from Equation 1. The dependent variable is Lender Share and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), return on equity ratio and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share				
	(1)	(2)	(3)	(4)	(5)
$CCPI_{lender}$	0.036*	0.045***	0.046***	0.046***	0.042***
	(0.019)	(0.008)	(0.009)	(0.008)	(0.008)
Bank Group Controls	✓	✓	✓	✓	✓
Borrower FE		✓	✓		
Year FE			✓		
Borrower × Year FE				✓	
Loan FE					✓
Obs.	11,671	11,671	11,671	11,671	11,671
R^2	0.006	0.740	0.742	0.812	0.844
Mean(Lender Share)	7.595				

As explained in Section 3, using granular fixed effects to control for loan demand requires an assumption that loan demand is constant across the lenders within the fixed effects level (Khwaja and Mian, 2008). This assumption is less likely to hold in a cross-border lending framework since borrowers may have lender-country-specific loan demand. However, since banks, except the lead arranger, participate in a syndicated loan after the loan terms are determined, the decisions of these banks are not affected by the borrower's loan demand, making the assumption valid. Specifically, comparing banks in the same loan would enable us to control the loan demand more precisely and identify the changes in loan supply more accurately. Therefore, we include loan fixed effects and compare two lenders of the same loan in column (5).[21] The magnitude of the coefficient in this within-loan model indicates that, as depicted in Figure A6, the loan share of the lender increases by 19.25 percent of the sample mean value when its home country's CCPI increases by 35 points—the difference between the UK and Australia in 2015. One possible loan demand-related concern could arise due to the endogenous borrower-lead arranger match. If lead arrangers invite participants from their local network, loan demand can influence the estimation through the borrower-lead arranger match. In Table A2, we assess the influence of this selection effect by removing the participants from the lead arrangers' country. We find results similar to our baseline evidence, alleviating such concerns.

After establishing that the positive relation between cross-border lending and policy stringency is not driven by loan demand, we now turn to the concern related to variables that are possibly correlated with both policy stringency and loan supply. This concern could arise, for instance, due to an improvement in the economic conditions. Better economic conditions can enable residents of a country to be more careful about the environment, leading to stringent climate policies while allowing banks to increase their cross-border lending. Moreover, cultural differences among the countries can be a factor in the observed heterogeneity in policy stringency.[22] In addition, demographic differences might explain heterogeneity in climate change awareness—a younger population can be more careful about the environment. Alternatively, the heterogeneity in policy stringency can be partially driven by legal and institutional differences across the countries. These variables can threaten our estimations to the extent that they are correlated with loan supply.

We mitigate the concern about the omitted variables with three exercises. First, we collect variables that are shown to be related to cross-border lending in the literature and include

[21]Note that loan fixed effects are more granular than borrower×year fixed effects since a borrower may obtain more than one loan in a year.

[22]Results from Round 8 of the European Social Survey show that there are variations in climate preferences and beliefs among the countries. For instance, residents in Israel, Norway, and Eastern European countries are less likely to think that climate change is caused by human activity (Poortinga et al., 2018).

them in our models. More specifically, in column (1) of Table 3, we include log(GDP per capita), domestic credit to GDP ratio, and the unemployment rate to control for economic conditions in the lender's home country. Next, we address lender country-level unobservables by constructing groups of countries belonging to the same regional area to include country-group and country-group×year fixed effects.[23] Thanks to these fixed effects, we compare lenders in the same loan from the same country groups in the same year, such as comparing one bank in Norway to another bank in Sweden in the same loan. To ensure that the results are not driven by the cultural proximity between the lender and the borrower, we include a dummy variable that takes the value of 1 if the lender and borrower country have the same language and log of the distance between these countries in column (4). We control for bank competition in the country by the market share of the largest five banks in the domestic market in column (5). We use population growth, and the share of old and young workforce in column (6) to capture the differences in demographics. The next column follows the literature and includes the property rights index and the log of contract enforcing days to control for the legal environment of the bank's home country (Qian and Strahan, 2007; Houston et al., 2012). Finally, we use indices of supervisory authority and capital regulation to control for bank regulation. In all of these specifications, the positive coefficient survives, and its magnitude is similar to the baseline results in Table 2.

Despite the rich set of control variables, the error term in Equation 1 can still be correlated with climate policy stringency, biasing our estimates. In the next exercise, we exploit the difference in policy stringency between the borrower and lender country to address this concern. As discussed in Section 4.2 in detail, our findings regarding the underlying mechanism indicate that banks use cross-border lending to decrease their exposure to climate policy stringency at home. These findings yield two predictions that could be useful in assessing whether the effect is driven by omitted variables. First, the increase in cross-border lending should be decreasing in the borrower's climate policy stringency. As the borrower's climate policy becomes more stringent, cross-border lending provides less evasion for the banks. Second, the increase in cross-border lending should occur only if the lender country's climate policy is more stringent than the borrower country's. Otherwise, increasing cross-border lending would not decrease but increase the lender's exposure to stringent climate policies. Confirming these predictions in our data may allow us to argue that the effect is not driven

[23] Country group consist of nine different country groups: Southern Europe (Portugal, Spain, Greece, Cyprus, Italy), Eastern Europe (Croatia, Ukraine, Poland), Western Europe (Austria, Belgium, France, Germany, Ireland, Luxembourg, Netherlands, Switzerland), Northern Europe (Finland, Denmark, Norway, Sweden), Anglo-Saxon countries (USA, Australia, New Zeland, Canada, UK), Emerging Far-East Asia (India, China, Malaysia, Thailand), Emerging Asia (Russia, Kazakhstan, Saudi Arabia, Turkey), Advanced Asia (Japan, South Korea, Taiwan, Singapore), and others (Brazil, Mexico, South Africa, Egypt).

Table 3: **Mitigating concerns about omitted variables**

This table reports estimates from Equation 1 but adding additional controls. The dependent variable is Lender Share and the main independent variable is $\text{CCPI}_{\text{lender}}$. The sample covers the period 2007-2017. Economic controls are log(GDP per capita), domestic credit to GDP, unemployment rate, and GDP growth. Country group fixed effects consist of nine different country groups: Southern Europe (Portugal, Spain, Greece, Cyprus, Italy), Eastern Europe (Croatia, Ukraine, Poland), Western Europe (Austria, Belgium, France, Germany, Ireland, Luxembourg, Netherlands, Switzerland), Northern Europe (Finland, Denmark, Norway, Sweden), Anglo-Saxon countries (USA, Australia, New Zeland, Canada, UK), Emerging Far-East Asia (India, China, Malaysia, Thailand), Emerging Asia (Russia, Kazakhstan, Saudi Arabia, Turkey), Advanced Asia (Japan, South Korea, Taiwan, Singapore), and others (Brazil, Mexico, South Africa, Egypt). Cultural controls are log(Distance) and common language. Domestic bank competition control is the Top 5 bank concentration. Demographic controls are log(total population), young workforce, old workforce, and population growth. Institution controls are the property rights index and log(Contract enforcing days). Bank regulation controls are independence of supervisory authority and capital regulatory index (Barth et al., 2013). Control variables and fixed effects are indicated at the bottom of each column. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{CCPI}_{\text{lender}}$	0.033***	0.036***	0.044***	0.038***	0.038***	0.043***	0.043***	0.038*
	(0.008)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.022)
Loan FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank Group Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country Group FE		✓						
Country Group × Year FE			✓	✓	✓	✓	✓	✓
Culture Controls				✓	✓	✓	✓	✓
Bank Competition Controls					✓	✓	✓	✓
Demography Controls						✓	✓	✓
Institutions Controls							✓	✓
Bank Regulation Controls								✓
Obs.	10,776	10,776	10,772	10,256	10,256	10,256	10,178	7,792
R^2	0.854	0.854	0.857	0.856	0.856	0.856	0.857	0.864
Mean(Lender Share)	7.595							

by an omitted variable since such an omitted variable has to be correlated with the borrower country's policy stringency in a way that generates these two implications, which is highly unlikely.

We test the first prediction on the first two columns of Table 4, where we interact the policy stringency of the lender country ($\text{CCPI}_{\text{lender}}$) with the stringency of the borrower country ($\text{CCPI}_{\text{borrower}}$). In line with the prediction, we estimate a negative coefficient for the interaction term, which suggests that a 10-unit increase in $\text{CCPI}_{\text{borrower}}$ reduces the increase in cross-border lending by approximately 40 percent. The remaining columns in Table 4 test the second prediction by splitting the sample into two in terms of the difference between $\text{CCPI}_{\text{lender}}$ and $\text{CCPI}_{\text{borrower}}$. We find that $\text{CCPI}_{\text{lender}}$ has a positive and statistically significant coefficient when $\text{CCPI}_{\text{lender}}$ is larger than $\text{CCPI}_{\text{borrower}}$. In contrast, it has an economically and statistically insignificant coefficient when $\text{CCPI}_{\text{lender}}$ is lower than $\text{CCPI}_{\text{borrower}}$. We can combine these two findings with Figure 1, where we use ΔCCPI, defined as the difference between $\text{CCPI}_{\text{lender}}$ and $\text{CCPI}_{\text{borrower}}$, on the x-axis and lender share

Table 4: **Cross-border lending and borrower climate policy stringency**

This table reports estimates from Equation 1. The dependent variable is Lender Share and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. Columns (1) and (2) include the interaction term $CCPI_{lender} \times CCPI_{borrower}$. Columns (2) to (6) show results when we split the sample in CCPI index of the lender's country higher/lower than the one of the borrower's country. Control variables, fixed effects, and the difference in estimated coefficients between split samples are indicated at the bottom of each column. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Interaction		$CCPI_{borrower} < CCPI_{lender}$			
	(1)	(2)	(3)	(4)	(5)	(6)
			Yes	No	Yes	No
$CCPI_{lender}$	0.048***	0.044***	0.062***	0.018	0.061***	0.016
	(0.008)	(0.008)	(0.015)	(0.016)	(0.016)	(0.017)
$CCPI_{lender} \times CCPI_{borrower}$	-0.002**	-0.002***				
	(0.001)	(0.001)				
Bank Group Controls	✓	✓	✓	✓	✓	✓
Borrower × Year FE	✓		✓	✓		
Loan FE		✓			✓	✓
Obs.	11,671	11,671	7,935	3,230	7,784	2,951
R^2	0.812	0.844	0.811	0.830	0.852	0.843
Mean(Lender Share)	7.595					
Difference			0.044***		0.045***	

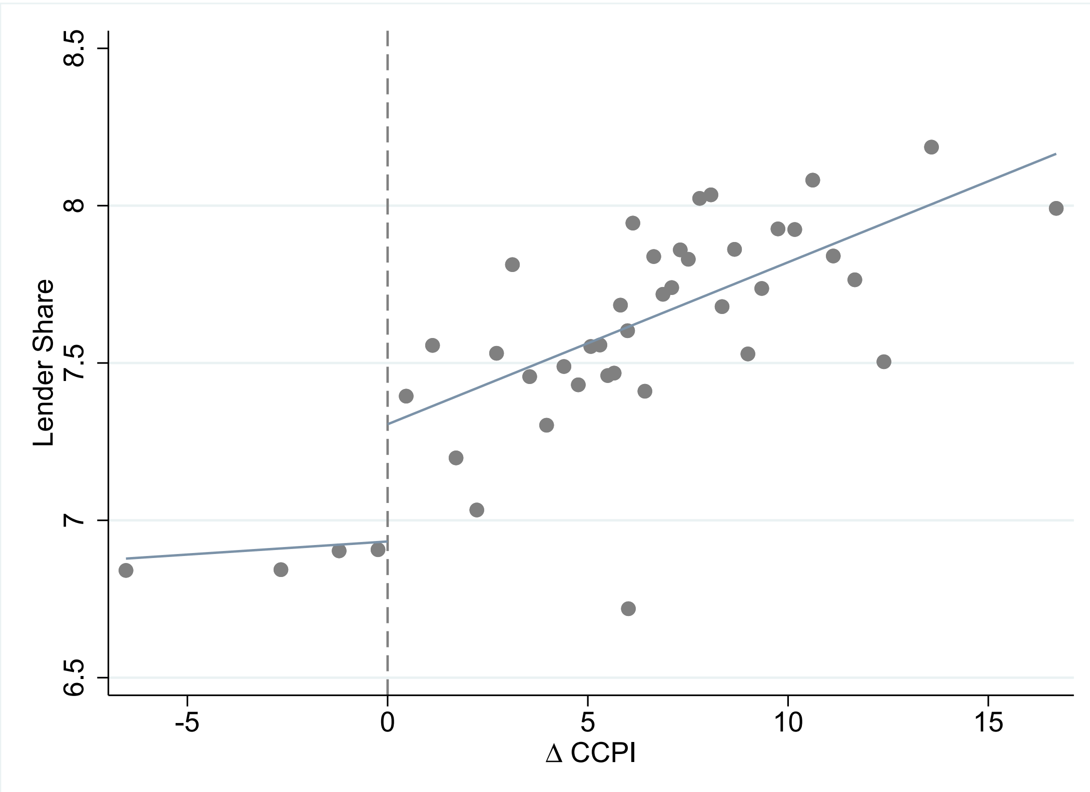
on the y-axis. Akin to regression discontinuity design, Figure 1 illustrates that the effect of domestic climate policy stringency on cross-border lending materializes only if the lender's country has a more stringent policy, and this effect increases in magnitude when ΔCCPI gets larger.

In the last exercise, we use the time a country's income level crosses a threshold as an instrument for policy stringency, which we refer to as time since industrialization. As discussed in Section 3, this instrument is likely to be relevant for policy stringency, owing to the environmental Kuznets curve concept. This concept states that a country will adopt stricter climate policies as it progresses in its economic development, which we measure by the log of the years since the GDP per capita of the country crosses USD 5,000. In line with this argument, column (1) of Table 5 shows that, indeed, policy stringency increases as time since industrialization increases.[24] After establishing that the first stage works as expected and is strong enough, we use the instrumented policy stringency as the main independent

[24]We use the efficient F-statistics developed by Olea and Pflueger (2013) to statistically assess the weak instrument problem. They propose a test for weak instruments robust to heteroscedasticity, serial correlation, and clustering. The first stage efficient F-statistics is 34.182 in our preferred specification, which is larger than the threshold level of 19.748 for a 10 percent worst-case benchmark derived by Olea and Pflueger (2013), alleviating the concerns about the weak instrument. The models in Columns (3) and (4) yield an F-stat of 10.995 and 10.585, respectively. The drop in the value is likely due to the demanding set of macroeconomic controls we include in the models.

Figure 1: **Difference in CCPI and Lender Share**

This figure shows that the positive effect of climate policy stringency does not exist if the borrower has a stringent climate policy, and the magnitude of the effect on loan supply increases as borrowers' climate policy becomes less stringent. The x-axis shows $\Delta CCPI$, which is defined as CCPI_{lender}-$\text{CCPI}_{borrower}$. The y-axis shows Lender Share. This figure uses residuals of a regression model, where Lender Share is regressed on loan fixed effects, bank group control variables (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), return on assets, and liquidity ratio). For variable definitions, see Table A1.



variable in column (2). In line with our previous results, the instrumented stringency has a positive and significant coefficient.[25]

Next, we assess the exclusion restriction in this setting. As argued in Section 3, the most likely way the exclusion restriction is to be violated is that the time since industrialization is correlated with economic conditions that are relevant to cross-border lending. If this is the case, the instrumented policy stringency could pick up the effect of these variables and

[25] The increase in the magnitude of the coefficient is related to the fact that the direction of the omitted variable bias (OVB) in our setting is unclear. Even though the main concern is that OVB could lead to overestimation, it can also lead to underestimation, if the omitted variable increases policy stringency and decreases cross-border lending. Therefore, an increase in the magnitude of the coefficient in the IV estimation is not unexpected in our setting. Regarding the inference of instrumented variables, Lee et al. (2022) report that the adjustment factor for instrumental variables is 1.376 when the 1^{st}-Stage F-statistics is 17.810. This adjustment factor indicates that the t-statistics of $\widehat{CCPI}_{\text{lender}}$'s coefficient should be larger than 1.173 to be significant at a 5 percent level. In column (2), the t-statistics of $\widehat{CCPI}_{\text{lender}}$ is 5.06, which means that the coefficient is significant at 5 percent.

Table 5: **Time of industrial development as an instrument for climate policy stringency**

This table reports estimates from Equation 1 in which CCPI is instrumented by the time of industrial development. The dependent variable is Lender share. The instrumental variable, ln(Years since $GDP_{pc}>5k$), is log of the years since GDP per capita of the country crosses five thousand dollars. The sample covers the period 2007-2017. Column (1) reports the first stage. Column (2) includes loan fixed effects. Column (3) includes economic condition controls. Column (3) includes trade-related controls. 1^{st} Stage Efficient F-statistics are calculated by the method developed by Olea and Pflueger (2013). Country control variables are GDP per capita, GDP growth, domestic credit to GDP ratio, and unemployment rate. Trade controls are trade openness and exchange rate changes. Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	$CCPI_{lender}$	Lender Share		
	(1)	(2)	(3)	(4)
ln(Years since $GDP_{pc}>5k$)	0.430***			
	(0.063)			
$\widehat{CCPI}_{lender}$		0.128***	0.083**	0.080**
		(0.025)	(0.034)	(0.034)
Economic Controls			✓	✓
Trade Controls				✓
Loan FE	✓	✓	✓	✓
Obs.	10,993	10,993	10,667	10,634
R^2	0.857	-0.025	0.008	0.008
1^{st} Stage Eff. F-stat	34.182			
Mean(Lender Share)	7.656			

yield biased estimates. We address this challenge by explicitly controlling for such economic conditions. Namely, we include $\log(\text{GDP})_{pc}$, $\Delta log(GDP)$, domestic credit to GDP ratio, and unemployment rate in column (2) and trade openness and exchange rate changes in column (3) of Table 5. In both models, we find positive and significant effects.

Despite the fact that including a battery of economic controls does not change our results, it is still possible that the exclusion restriction does not hold exactly. Due to this possibility, we relax the exclusion restriction assumption with the method developed by Conley et al. (2012). The exclusion restriction in our setting means that the effect of the time since industrialization on cross-border lending is assumed to be zero after controlling for its effect through the climate policy stringency. Formally, the exclusion restriction corresponds to assuming that $\gamma = 0$ in the following regression model: $Lender\ share = \beta\ CCPI + \gamma\ ln(Years\ since\ GDP_{pc} > 5k) + \epsilon$. The plausibly exogenous instrumental variable method by Conley et al. (2012) provides interval estimates for β when γ deviates from being exactly zero. Intuitively, these interval estimates show how large the direct effect of

$ln(Years\ since\ GDP_{pc} > 5k)$ (γ) should be to make the effect of $CCPI$ (β) insignificant. We report the results of this method in Figure A7 at a 10 percent significance level for β, in which the x-axis shows different values of γ and the y-axis depicts the corresponding intervals for β. Figure A7 illustrates that the direct effect of the time since industrialization should be as large as its effect through climate policy stringency to make β insignificant at 10 percent. Considering the fact that this policy already controls for the relevant economic conditions, we deem this implausible. Overall, our findings provide consistent evidence that indicates a positive and causal effect of climate policy stringency on banks' cross-border loan supply.[26]

4.2 Mechanism

So far, our results show that a more stringent climate policy leads to an increase in cross-border lending. This section investigates the underlying mechanism and provides evidence that banks use cross-border lending to facilitate race to the bottom behavior. The race to the bottom in the international banking context means that after facing stricter regulation in their home country, banks shift their activities from their home country to countries with looser regulation, which enables them to evade the more stringent regulation at home (Acharya, 2003; Houston et al., 2012; Karolyi and Taboada, 2015). In our context, this mechanism occurs since climate policies prompt a reallocation of resources that may hurt some firms, which has two main implications. First, stricter climate policies may make domestic lending less appealing due to the possible adverse effects of stricter policies on banks' loan portfolios. Second, banks engage with cross-border lending if doing so enables banks to circumvent these adverse effects.

We start our analysis by investigating the first implication: do stricter climate policies make domestic lending less appealing? Stricter climate policies aim to reduce the carbon print of the economy, which entails a reduction in carbon emissions. A reduction in emissions may require a reallocation of resources that influences the relative prices of the factors. In addition, it may entail a change in the business model or the production process within a firm. Also, existing inventories and machinery may lose value due to the needed changes (Litterman, 2021). These suggest that a stringent climate policy may worsen some of the domestic firms' economic prospects, making domestic lending less appealing.

[26] In an additional test, we the Green Party share in national parliaments as an instrument for climate policy stringency and again find a positive effect on cross-border lending Table A3. The main idea of this IV is that the Green Party share satisfies the relevance condition thanks to the focus of these parties on environmental problems. In addition, the Green Party share changes only after elections, indicating that the exclusion restriction may be satisfied if the predetermined nature of election cycles eliminates the association between the share and omitted variables.

One direct way to assess this channel is by looking at the relationship between climate policy stringency and the performance of banks' loan portfolios. To this end, we regress banks' nonperforming loans and return on assets on policy stringency in Table 6. In this table, we use all banks in each country, both the ones that engage and do not engage with cross-border lending. We find that policy stringency is positively associated with the nonperforming loans ratio and negatively associated with banks' profits, which creates motives for banks to perform a race to the bottom.[27] Specifically, Table 6 documents that as CCPI increases by one standard deviation, NPL ratios increase by 0.3 pp (6 percent of the sample mean), and return on assets decreases by 0.53 pp (11 percent of the sample mean). As explained before, the race to the bottom behavior suggests that banks engage with cross-border lending to mitigate these adverse effects. Therefore, the effect of climate policy stringency on loan portfolios can be different for cross-border lenders. To test this, we create a dummy variable that takes the value of one if a bank extends a cross-border loan in a year in our sample and interact this dummy with policy stringency. Indeed, we find that the interaction term has the opposite sign of the direct effect—it is negative for nonperforming loans and positive for bank profits. These results indicate that climate policies hurt banks' loan portfolios, and cross-border lending enables banks to circumvent the adverse effects of climate policies.

The negative association between policy stringency and banks' loan portfolios raises a related question of how policy stringency influences domestic loan demand. A lower loan demand at home could explain the increase in cross-border loan supply and worsening banks' loan portfolio performances. Even though the needed changes induced by stricter policies suggest higher loan demand by domestic firms, policy stringency could also lower the loan demand, for instance, if it affects economic activity negatively. We regress domestic loan spread on policy stringency at home in Table 7 to assess whether the demand or the supply plays a role in our results. A decline in loan demand suggests a decline in the spread, whereas a decline in supply suggests an increase in the spread. Our findings in Table 7 are in line with a decrease in loan supply and thus with the race to the bottom mechanism: the loan spread at home country increases as the climate policy becomes more stringent.

So far, we have separately shown that stringent climate policies at home increase banks'

[27] To explain these adverse effects, we relate firm profitability to climate policy stringency in the Appendix Table A4. Confirming the negative impact on banks' loan portfolios, we again find that climate policy stringency is negatively correlated with firms' profits. Specifically, we use Return on Equity, Return on Capital, Net Profit Margin, and Operating Margin as firm profit indicators at the country level. We use the aggregate values obtained from Aswath Damodaran's website. The profit variables are calculated at the firm level for only public firms and then aggregated up to the country-year level. These aggregate values are, therefore, less susceptible to outliers.

cross-border lending to borrowers located in countries with less strict policies while worsening banks' domestic loan portfolios and thereby reducing their domestic loan supply. In what follows, we combine these two findings and simultaneously test the two implications of the race to the bottom mechanism. The race to the bottom mechanism suggests that a more stringent climate policy can make lending to borrowers with high carbon risks less appealing. Therefore, this mechanism predicts a decline in lending to domestic borrowers with high carbon risk. At the same time, this mechanism predicts that banks may increase their cross-border lending to borrowers with high carbon risk since banks may prefer replacing their high-risk domestic borrowers with comparable borrowers abroad. We combine cross-border lending with domestic lending to assess these two predictions together. In addition, we collect information about firm-level carbon intensity risk. The carbon intensity risk shows how much a firm is exposed to unmanaged carbon risk based on emissions level.[28] These additional data allow us to create two dummy variables. The first dummy variable, *same country*, takes the value of 1 if the loan is domestic. The second dummy variable, *high carbon intensity risk*, equals one if the borrower is defined as a high, severe, or medium carbon risk firm. We interact these two dummy variables with $\text{CCPI}_{\text{lender}}$ and report the results in Table 8. In line with the mechanism, high carbon intensity risk$\times\text{CCPI}_{\text{lender}}$ has a positive

Table 6: **Climate policy stringency and banks' loan portfolios**

This table documents that domestic climate policy stringency is positively correlated with lenders' nonperforming loans ratio, and negatively correlated with lenders' return on assets. *Cross-Border Lender* is a dummy variable that takes the value of 1 if the lender engages in cross-border lending in our sample. Data used in this table covers all banks that operate domestically and/or internationally. Columns (1)-(3) use the nonperforming loans ratio as the dependent variable. Columns (4)-(6) use banks' return on assets as the dependent variable. Control variables and fixed effects are indicated at the bottom of each column. Control variables are GDP growth, unemployment rate, GDP per capita, exchange rate, and domestic credit to GDP ratio. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Nonperforming Loans Ratio				Return on Assets			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{CCPI}_{\text{lender, t-1}}$	0.032**	0.031*	0.037**	0.013	-0.202***	-0.064**	-0.066**	-0.058**
	(0.014)	(0.017)	(0.016)	(0.022)	(0.043)	(0.026)	(0.029)	(0.028)
$\text{CCPI}_{\text{lender, t-1}}$ × Cross-Border Lender				-0.060**				0.367*
				(0.024)				(0.206)
Controls			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓				✓			
Bank FE		✓	✓	✓		✓	✓	✓
Obs.	24,297	23,434	23,216	23,076	179,659	178,126	177,076	176,129
R^2	0.318	0.943	0.943	0.943	0.085	0.511	0.510	0.510
Mean(Dep. Var.)	4.893				4.464			

[28]We gather data from Sustainalytics. Due to data availability of firm-level carbon risk, the number of observations declines in this sample.

Table 7: **Climate policy stringency and domestic loan spread**

This table reports estimates, in which the dependent variable is loan spread and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017 and consists of banks that operate in the domestic syndicated loans market. Loan spread is obtained from syndicated loans. Bank group controls are net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Country controls are GDP per capita), domestic credit to GDP, unemployment rate, and GDP growth. Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Loan Spread			
	(1)	(2)	(3)	(4)
$CCPI_{lender}$	3.146**	3.804***	1.273	2.429**
	(1.240)	(1.145)	(0.996)	(1.167)
Bank Group Controls		✓	✓	✓
Country Controls			✓	✓
Country FE				✓
Obs.	11,819	11,819	8,626	8,625
R^2	0.032	0.115	0.171	0.225
Mean(Dep. Var.)	171.206			

coefficient, which means that climate policy stringency increases cross-border lending more if the borrower has a high carbon risk. In addition, we estimate a negative coefficient for the same country×high carbon intensity risk×$CCPI_{lender}$. This negative coefficient shows that credit supply to domestic firms decreases when $CCPI_{lender}$ increases if the domestic firm has a high carbon risk.

A corollary of the race to the bottom mechanism in our context is that banks should extend cross-border loans to borrowers who are similar to their domestic borrowers. The reason is that lending to similar borrowers reduces both screening and monitoring costs, making cross-border lending easier for banks. To test this, we turn to banks' domestic syndicated loans and use these loans to calculate bank specialization. Namely, we calculate each industry's share in banks' domestic lending. Then, we assume that a bank specializes in an industry if this industry has the largest share in its domestic loans. We use this specialization variable to create a dummy variable, *specialized loan*, that takes the value of 1 if the cross-border loan is in the banks' specialized industry. In the first three columns of Table 9, we regress the *specialized loan* dummy on policy stringency with different control variables. We find that banks lend more specialized cross-border loans as policy stringency increases, suggesting that banks aim to conserve the industrial composition of their loan portfolios. Moreover, banks may increase their supply more when they lend specialized loans.

Table 8: **Does a stricter climate policy change the supply of credit domestically?**

This table reports estimates from Equation 1. The dependent variable is Lender Share and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. All columns include the triple interaction term, $CCPI_{lender}$×Same Country×High Carbon Intensity Risk, where High Carbon Intensity Risk is a dummy variable equal to 1 if the firm is assigned to a High, Severe, or Medium Carbon Risk category according to the final carbon risk score (high-level polluting firms) and 0 otherwise (Negligible or Low Carbon Risk Category); Same Country is a dummy variable equal to 1 if the lender and the borrower are located in the same country (domestic loan) and 0 otherwise. Control variables and fixed effects are indicated at the bottom of each column. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Carbon-intensive firms				
	(1)	(2)	(3)	(4)	(5)
Same Country × High Carbon Intensity Risk × $CCPI_{lender}$	-0.317**	-0.353***	-0.344***	-0.234**	-0.234**
	(0.125)	(0.110)	(0.111)	(0.097)	(0.096)
Same Country × High Carbon Intensity Risk	19.355***	19.198***	18.794***	11.999**	11.733**
	(7.041)	(6.585)	(6.619)	(5.664)	(5.672)
High Carbon Intensity Risk × $CCPI_{lender}$	0.085	0.070	0.077	0.104**	0.083*
	(0.085)	(0.068)	(0.065)	(0.044)	(0.043)
Same Country × $CCPI_{lender}$	0.066	0.086	0.079	0.011	0.023
	(0.101)	(0.125)	(0.126)	(0.099)	(0.107)
Same Country	-1.752	-2.171	-1.784	2.550	1.799
	(5.998)	(7.491)	(7.539)	(5.939)	(6.354)
High Carbon Intensity Risk	-4.178	-0.698	-1.201		
	(5.066)	(4.887)	(4.680)		
$CCPI_{lender}$	-0.022	0.012	0.002	-0.023	-0.021
	(0.067)	(0.069)	(0.067)	(0.045)	(0.044)
Bank Group Controls	✓	✓	✓	✓	✓
Borrower FE		✓	✓		
Year FE			✓		
Borrower × Year FE				✓	
Loan FE					✓
Obs.	2,540	2,540	2,540	2,540	2,540
R^2	0.073	0.540	0.543	0.612	0.701
Mean(Lender Share)	9.008				

Indeed, interacting *specialized loan* dummy with policy stringency in the last three columns of Table 9 reveals that banks almost double their loan shares if the loan is specialized.

One prediction related to the race to the bottom mechanism is that climate policy-induced cross-border lending should not be affiliated with lower emissions by cross-border borrowers since this mechanism does not suggest that banks should impose a restriction on their borrowers' emissions. To test this, we regress cross-border borrowers' emissions on exposure to climate policy from cross-border lending, which is the weighted average of policy stringency where the weights are cross-border loan amounts. Even though the number of observations is low due to data availability, Table A5 shows no effect on borrower emissions, thus confirming the race to the bottom mechanism.

Next, we consider two indirect implications of the race to the bottom mechanism in the context of climate policy. The first indirect implication is about the bank's reputation. Due to the public pressure for climate policies, the race to the bottom may be perceived negatively

Table 9: **Climate policy stringency and specialized loans**

This table documents that lenders extend more specialized cross-border loans as the climate policy stringency in their home countries becomes more stringent, and the positive effect of climate policy stringency on cross-border lending is stronger for specialized loans. *Specialized Loan* is a dummy variable that takes the value of 1 if a borrower is in the banks' specialized industry. Lenders' specialized industry is the industry that received the highest loan amount from the lender last year in the domestic syndicated loan market. Columns (4)-(6) of Table 9 use *Specialized Loan* as the dependent variable. Columns (1)-(3) of Table 9 interact $CCPI_{lender}$ with *Specialized Loan*. Control variables and fixed effects are indicated at the bottom of each column. Bank Group controls are log(total assets), net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio and their interaction with *Specialized Loan*. Country Controls are GDP growth, unemployment rate, GDP per capita, and domestic credit to GDP ratio. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Specialized Loan			Lender Share		
	(1)	(2)	(3)	(4)	(5)	(6)
$CCPI_{lender}$	0.007***	0.005***	0.005**	0.043***	0.030***	0.022**
	(0.002)	(0.002)	(0.002)	(0.007)	(0.008)	(0.009)
$CCPI_{lender}$ × Specialized Loan				0.034**	0.041**	0.031*
				(0.014)	(0.017)	(0.018)
Bank Group Controls		✓	✓		✓	✓
Country Controls			✓			✓
Loan FE	✓	✓	✓	✓	✓	✓
Obs.	11,671	11,671	10,776	11,671	11,671	10,776
R^2	0.476	0.480	0.479	0.842	0.844	0.855
Mean(Dep. Var.)	0.300			7.595		

and hurt banks' publicity. Therefore, banks may prefer increasing their cross-border lending to countries where the flow of information is less likely to reach their home country. In Panel A of Table 10, we use the distance between the lender and borrower countries and whether the lender and borrower countries share a border or have the same language as a proxy for information flow possibilities. In line with the possible adverse effects of race to the bottom on banks' publicity, banks increase their cross-border lending more if the borrower country does not have the same language or share a border with the lender country. In addition, the increase in cross-border lending is driven by lender-borrower pairs that have larger distances above the sample's median value. The second indirect implication is about the bank supervision environment of lender countries. Due to political pressure, a race to the bottom behavior may attract the attention of the bank supervisory authorities with a possible penalty on banks. Therefore, banks may be more likely to pursue such behavior in a weaker supervision environment. We test this hypothesis in Panel B of Table 10, using two different bank supervision environment variables. Namely, we use *independence of the bank supervisory authority*. This variable shows the degree to which the supervisory authority is independent of the government and legally protected from the banking industry. In the last three columns, we use *bank supervisory power*, which measures whether the supervisory authorities have the authority to take specific actions to prevent and correct problems (Barth et al., 2013). Higher values indicate higher power/authority for both of these variables. By splitting our sample into three, we see that the increase in cross-border lending is stronger if the lender country's bank supervision has low independence or low power. These two heterogeneity tests suggest that strong bank regulation may complement climate policies and also support the race to the bottom mechanism as the main driver of our results.

Table 10: **The role of bank reputation and bank regulation**

This table documents that the increase in cross-border lending is larger when the bank reputation is less likely to be affected and when the bank regulatory authority has less power. The dependent variable is Lender Share and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. In Panel A, Columns (1) and (2) split the sample into two with respect to the languages of the lender and borrower countries. Columns (3) and (4) split the sample into two with respect to the distance between the lender and borrower countries. Columns (5) and (6) split the sample into two, considering whether the lender and borrower countries share borders. In Panel B, the first three columns split the sample in terms of the *Independence of the Bank Supervisory Authority*. The last three columns split the sample in terms of *Bank Supervisory Power*. Control variables and fixed effects are indicated at the bottom of each column. Bank group control variables are net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Bank Reputation

Lender Share	Language		Distance		Border	
	(1) Diff.	(2) Same	(3) High	(4) Low	(5) No	(6) Yes
$CCPI_{lender}$	0.043***	0.035**	0.072***	0.007	0.051***	0.008
	(0.010)	(0.013)	(0.012)	(0.012)	(0.009)	(0.043)
Bank Group Controls	✓	✓	✓	✓	✓	✓
Loan FE	✓	✓	✓	✓	✓	✓
Obs.	8,601	1,723	5,766	4,587	10,072	1,030
R^2	0.856	0.827	0.822	0.885	0.838	0.939
Mean(Lender Share)	7.595					
Difference	-0.025		0.037*		-0.056	

Panel B: Bank Regulation

Lender Share	Bank Supervisory Power			Bank Supervisory Auth.		
	(1) Low	(2) Medium	(3) High	(4) Low	(5) Medium	(6) High
$CCPI_{lender}$	0.066***	0.035*	0.008	0.072***	0.047	0.027**
	(0.025)	(0.020)	(0.021)	(0.021)	(0.065)	(0.011)
Bank Group Controls	✓	✓	✓	✓	✓	✓
Loan FE	✓	✓	✓	✓	✓	✓
Obs.	2,347	2,326	2,741	2,948	2,184	2,910
R^2	0.828	0.868	0.870	0.873	0.852	0.861
Mean(Lender Share)	7.595			7.595		

We conclude this section by exploring the role of banks' domestic borrowers in explaining the underlying mechanism. Suppose firms react to a stringent climate policy at home by moving their activities abroad via their subsidiaries. In that case, banks may follow these domestic borrowers by lending to their foreign subsidiaries, effectively increasing cross-border lending. To test the role of domestic borrowers, we first obtain parent-subsidiary information from the Orbis database and match this information to syndicated loan data. Then, we create a dummy variable, *subsidiary lending*, that is equal to one if the bank has a lending relationship with the parent company of the cross-border borrower in the bank's domestic market. We regress *subsidiary lending* on policy stringency in Table A6. We find that stricter climate policy increases the probability of lending to a subsidiary of a domestic borrower in the cross-border loan market, yet the effect becomes insignificant when we add control variables and is small in magnitude—a six-point increase in policy stringency increases subsidiary lending by only 18 basis points. Considering that the mean of subsidiary lending in our sample is 11 percent, we deem this effect too small to play a major role in the underlying mechanism. To sum up, our results illustrate a clear picture, in which banks use cross-border loans for race to the bottom behavior, possibly reducing the effectiveness of climate policies of their home countries.

4.3 Additional analysis

This section continues our analysis by providing additional findings. First, we investigate which component of the CCPI is more important for the increase in cross-border lending. As explained in Section 2, CCPI consists of four main categories: GHG emissions improvement, renewable energy, energy efficiency, and climate policy. Climate policy captures governments' policy actions against climate change, and it is the initial point of the fight against climate change. The climate policies are expected to affect energy use and renewable energy categories, which, in turn, are expected to lower GHG emissions. Investigating which of these categories is the main driver of our results is informative about banks' cross-border lending behavior. For instance, if banks anticipate the consequences of policies, the policy component could be the main driver. On the other hand, if banks wait to react until they observe changes in firm performances, such as lower profitability due to climate policies, the other components could be the main factors. We regress lender share on each of these components one by one in columns (1) to (4) in Table 11 and find that all categories have positive and significant coefficients separately. In the last two columns, we run horse race models with all four categories included as explanatory variables. In these models, only the climate policy has a statistically significant coefficient, suggesting that banks anticipate the consequences of climate policies and adjust their lending accordingly.[29]

Second, we explore the heterogeneity in lender characteristics in Table 12. In columns (1)

[29] We replicate our main table by using the climate policy component in Table A7 and find slightly larger effects. Moreover, we replicate all of our tables by using the climate policy component and find similar results.

Table 11: **Which component of the CCPI matters most?**

This table reports estimates from Equation 1 in which parts of CCPI are used as explanatory variables. The dependent variable is Lender Share. The sample covers the period 2007-2017. Control variables and fixed effects are indicated at the bottom of each column. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share				
	(1)	(2)	(3)	(4)	(5)
Climate policy$_{lender}$	0.057***				0.057***
	(0.012)				(0.012)
Renewable energy$_{lender}$		0.111**			0.055
		(0.048)			(0.052)
Energy efficiency$_{lender}$			0.124***		0.061
			(0.038)		(0.077)
$CO_{2lender}$				0.039***	0.028
				(0.013)	(0.022)
Bank Group Controls	✓	✓	✓	✓	✓
Loan FE	✓	✓	✓	✓	✓
Obs.	11,671	11,671	11,671	11,671	11,671
R^2	0.843	0.843	0.843	0.843	0.844
Mean(Lender Share)	7.595				

and (2) of Table 12, we split our sample in terms of bank size. For larger banks, increasing cross-border lending as a reaction to more stringent climate policy is easier since the fixed costs attached to cross-border lending can be less important for such banks. In line with this intuition, we find that the increase in cross-border lending is stronger for larger banks. Similarly, for banks with more experience in cross-border lending, exploiting cross-border lending as a reaction to climate policy should be easier. This is indeed what our results show in columns (3) and (4). The increase in cross-border lending is almost five times larger for the banks whose cross-border loan ratios are above our sample's median. The next two columns split the sample into two with respect to bank capital. Even though the effect is larger for less capitalized banks, the difference is not statistically significant. Columns (5) and (6) divide our sample with respect to capital. Banks with lower capital may suffer from agency problems, leading to a higher incentive for race to the bottom behavior. Indeed, the effect is larger for low-capitalized banks. Next, we investigate the influence of banks' NPL ratio on the effect of climate policy stringency. The race to the bottom mechanism has a special prediction for the NPL ratio, which is that the effect can be stronger for banks with a high NPL ratio. The reason is that these banks are more in need of profits. Thus, the incentive for them to increase cross-border lending must be stronger. In line with this argument, we find that the effect is significantly larger for banks with a high NPL ratio. Last, we investigate whether the effect depends on the role of the lender in the syndicated loan. Columns (9) and (10) of Table 12 show that the effect is similar for lead arrangers and participants.

Table 12: **How does the effect differentiate with respect to lenders' characteristics?**

This table reports estimates from Equation 1. The dependent variable is Lender Share and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. Columns (1) and (2) split the sample into two with respect to bank size (above/below total assets sample median). Columns (3) and (4) split the sample into two with respect to the ratio of cross-border lending to total lending (above/below the sample median). Columns (5) and (6) split the sample into two with respect to the Tier 1 capital ratio (above/below sample median). Columns (7) and (8) split the sample into two with respect to the non-performing loans ratio (NPL) (above/below sample median). Columns (9) and (10) split the sample into two with respect to the lead bank and participant banks following the definition by Ivashina (2009). Split points are the sample's median values. Control variables, fixed effects, and the difference in estimated coefficients between split samples are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Size		Cross-Border		Capital		NPL		Lead bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Low	High	Low	High	Low	High	Low	High	Yes	No
$CCPI_{lender}$	0.024***	0.054***	0.023***	0.108***	0.066***	0.039***	0.020	0.051*	0.046***	0.045***
	(0.009)	(0.010)	(0.009)	(0.016)	(0.012)	(0.008)	(0.014)	(0.027)	(0.013)	(0.007)
Loan FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	4,941	5,046	5,039	5,043	5,106	5,183	779	776	1,722	9,382
R^2	0.840	0.858	0.839	0.842	0.844	0.866	0.854	0.731	0.846	0.869
Mean(Lender Share)	7.595									
Difference	0.031***		0.086***		-0.027***		0.031		0.001***	

Next, we study the regional patterns in the effect of climate policy stringency. Studying the regional patterns can be particularly interesting as it would show the direction of climate policy-induced cross-border lending. Given the distribution of CCPI across the world, we focus on Europe and report the results in which we use only European lenders in Table 13. This table categorizes borrowers into five locations: the U.S., emerging markets, Europe, Asia, and Anglo-Saxon countries. Among these five groups, the positive effect of climate policy stringency on cross-border lending is strongest for emerging markets. At the same time, the estimated effect is insignificant and small in size when the borrowers are located in the USA and Europe. This suggests that European lenders channel their credit supply towards emerging markets due to a more stringent climate policy at home.

We also study the influence of loan terms on the effect on cross-border lending. To this end, we interact policy stringency with maturity, spread, and covenant in Table A8. None of these interaction terms is significant, suggesting that banks use the loan amounts as their main tool to react to stricter climate policies at home. Last, we assess if time effects influence our main finding. To see this, we run six-year rolling window regressions and plot the coefficients in Figure A8. The coefficients indicate that coefficients are not statistically different from each other, suggesting that time effects, such as different macroeconomic

Table 13: **The effect of home country climate policy on cross-border lending: Are there regional patterns?**

This table reports estimates from Equation 1 in which we cluster countries in the same geographical area. The dependent variable is Lender Share and the main independent variable is $\text{CCPI}_{\text{lender}}$. The sample covers the period 2007-2017. European countries are Austria, Belgium, Denmark, France, Germany, Greece, Netherlands, Ireland, Italy, Norway, Spain, Portugal, and the United Kingdom. Emerging market countries are Saudi Arabia, China, Chinese Taipei, India, Brazil, the Russian Federation, Indonesia, South Africa, Malaysia, and Turkey. Asian countries are Japan, Singapore, Korea, Chinese Taipei, and China. Anglo-Saxon countries are the United States, Canada, Australia, and New Zealand. All lenders in this table are located in Europe. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables, fixed effects, and the difference in estimated coefficients between split samples are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Europe vs USA	Europe vs Emer. mark.	Europe vs Europe	Europe vs Asia	Europe vs Anglo-Saxon
	(1)	(2)	(3)	(4)	(5)
$\text{CCPI}_{\text{lender}}$	0.029	0.131***	0.016	0.111	0.040*
	(0.026)	(0.032)	(0.017)	(0.070)	(0.023)
Bank Group Controls	✓	✓	✓	✓	✓
Loan FE	✓	✓	✓	✓	✓
Obs.	3,751	885	3,057	373	4,091
R^2	0.820	0.894	0.903	0.864	0.833
Mean(Lender Share)	7.595				

conditions, do not matter for our results.

4.4 Robustness

The last section examines the sensitivity of our results to alternative measures and starts with considering different climate policy indices. While CCPI is suitable for our research question as explained in Section 2, our results could partially depend on how CCPI is constructed and, therefore, have limited external validity. To assess whether our results extend to other climate policy measures, we estimate our main model with three other policy indices in Table 14. The first index is the Climate Change Cooperation Index (C3-I) by Bernauer and Böhmelt (2013). The main difference between C3-I and CCPI is that C3-I uses countries' ratification for standard climate policies, such as UNFCCC, and Kyoto Protocol, to measure climate policy strictness. The second index is the OECD's Environmental Policy Stringency Index (EPS). Similar to C3-I, and unlike CCPI, EPS also focuses only on a set of climate policies, such as CO_2 trading schemes, and aggregates these policies up to a single index (Kruse et al., 2022). The last index is the Environmental Performance Index (EPI), developed jointly by the World Economic Forum, European Commission, Yale, and Columbia Universities (Hsu et al., 2016). While covering a longer time period, EPI is a biennial index and consists of policies regarding climate change, energy consumption, and biodiversity. These three indices focus on different aspects of climate policies and have correlations with CCPI lower than 50 percent. Despite these differences, all three indices confirm our main finding: banks increase their cross-border lending as their home countries implement stricter climate policies (Table

14). As explained in Section 2, our sample ends in 2017 due to a small methodological change in CCPI and COVID-19. In Table A9, we replicate our main table with a sample extended to 2023 and find virtually the same results.

Table 14: **Alternative indices for home country climate policy stringency**

This table investigates the relationship between cross-border lending and home country climate policy stringency using alternative country-level indices. The dependent variable is Lender Share. In columns (1)-(2), the index is the Climate Change Cooperation Index (C3-I) by Bernauer and Böhmelt (2013). In columns (3)-(4), the index is the OECD Environmental Policy Stringency Index (EPS). In columns (5)-(6), the index the Environmental Policy Index developed by YCELP, CIESIN, and the World Economic Forum (Hsu et al., 2016). The sample covers the period 2007-2014 in columns (1) and (2), 2007-2017 in columns (3) and (4), and 2007-2016 in columns (5) and (6). Bank controls are Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio. Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{C3-I}_{\text{lender}}$	0.149**	0.157*				
	(0.071)	(0.094)				
$\text{EPS}_{\text{lender}}$			0.465***	0.176*		
			(0.079)	(0.105)		
$\text{EPI}_{\text{lender}}$					0.077***	0.066***
					(0.011)	(0.011)
Bank Group Controls		✓		✓		✓
Loan FE	✓	✓	✓	✓	✓	✓
Obs.	1,697	1,697	10,949	10,949	10,790	10,790
R^2	0.818	0.828	0.854	0.855	0.843	0.845
Mean(Index)	54.561		3.234		83.068	
Mean(Lender Share)	6.574		7.640		7.723	

In the next robustness check, we use loan amounts as the dependent variable instead of lender shares. The concern about using the lender share is that if the loan size gets smaller as climate policy becomes more stringent, the amount of lending of a bank to a borrower can be smaller, even though the loan share is higher. To alleviate this concern, we use the loan amount (logarithm) as the dependent variable in our main model in Table A10. Similar to our main table, we saturate the model with the loan fixed effects and estimate a positive and significant coefficient, confirming the positive impact of climate policy stringency on cross-border lending.

Next, we aggregate our loan level data up to the bank-borrower country level, following De Haas and Van Horen (2013). Even though the granularity of the loan level data is valuable for identification, it can mask some patterns at the aggregate level. For instance, an increase in policy stringency may decrease the number of cross-border loans, and this decrease can offset the increase in loan shares caused by policy stringency. To see whether such a pattern emerges in our sample, we use two aggregated lending variables at the bank-borrower country level: the number of syndicated loans a bank extends to a country, and the total amount of loans a bank extends to a country. We use the logarithm of the number of loans as the dependent variable in the first four columns of Table 15 and the logarithm of the loan amount in the remaining four columns. Importantly, in addition to $\text{CCPI}_{\text{lender}}$, we use ΔCCPI as the main independent variable, which is the difference between $\text{CCPI}_{\text{lender}}$ and $\text{CCPI}_{\text{borrower}}$ in Panel B of Table 15. We follow Khwaja and Mian (2008) and De Haas and Van Horen (2013) and control for loan demand with borrower country$\times$year fixed effects and include bank-level characteristics as control variables. Intuitively, we compare the lending of two banks with different $\text{CCPI}_{\text{lender}}$ or ΔCCPI to the same borrower country. Note that when we include borrower country$\times$year fixed effects, $\text{CCPI}_{\text{lender}}$ and ΔCCPI have exactly the same coefficients since borrower country$\times$year fixed effects absorb all variation at the borrower country level, including $\text{CCPI}_{\text{borrower}}$. In these alternative specifications, we estimate positive and significant coefficients for the number of loans and loan amount, confirming that our main result holds in the aggregate.[30]

Last, we follow the literature and populate the missing loan shares by allocating the total amount of unreported loan shares equally across lenders who do not report a share (Doerr and Schaz, 2021; De Haas and Van Horen, 2013; Giannetti and Laeven, 2012).[31] We again estimate a positive and significant effect on climate policy, as shown in Table A11.

[30]We assess the robustness of our results at an aggregate level using the Bank for International Settlements (BIS) locational banking statistics (LBS) on total cross-border banking activity measured as total bank assets abroad. Our analysis reveals no statistically significant changes attributable to the stringency of domestic climate policy, which directly impacts corporations and, in turn, indirectly banks. This finding is unsurprising, as cross-border banking activity between countries often occurs between banks and is influenced by numerous factors unrelated to climate policy. Notably, previous studies have utilized this dataset in the context of banking regulations (Houston et al., 2012; Ongena et al., 2013), or policies that directly impact banks.

[31]Approximately, we can observe the loan shares for 28 percent of the loans.

Table 15: **Climate policy stringency differentials and cross-border credit flows**

This table shows estimation results from the bank-country pair's analysis –bank-country level regressions– and effects on cross-border credit flows. We study the number (first four columns) and the volume (last four columns) of cross-border lending from bank i to country j –the country where borrower companies are located. The dependent variables are log(1+loan amount) (Volume) or log(1+number of loans) (Number) and the main independent variables $CCPI_{lender}$ and $\Delta CCPI$, which is equal to the difference between $CCPI_{lender}$ and $CCPI_{borrower}$. The sample covers the period 2007-2017. Columns (4) and (8) include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the country-pair level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Panel A

	Number				Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CCPI_{lender}$	0.029***	0.034***	0.036***	0.028***	0.074***	0.070***	0.073***	0.057***
	(0.008)	(0.005)	(0.005)	(0.005)	(0.013)	(0.010)	(0.010)	(0.011)
Bank Group Controls				✓				✓
Borrower country FE		✓				✓		
Borrower country × Year FE			✓	✓			✓	✓
Obs.	4,211	4,208	4,185	4,185	4,211	4,208	4,185	4,185
R^2	0.042	0.275	0.318	0.354	0.081	0.237	0.309	0.372
Mean(dep. var.)	2.198				19.495			

Panel B

	Number				Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta CCPI$	0.025***	0.028***	0.036***	0.028***	0.029***	0.055***	0.073***	0.057***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.008)	(0.009)	(0.010)	(0.011)
Bank Group Controls				✓				✓
Borrower country FE		✓				✓		
Borrower country × Year FE			✓	✓			✓	✓
Obs.	4,211	4,208	4,185	4,185	4,211	4,208	4,185	4,185
R^2	0.058	0.265	0.318	0.354	0.024	0.222	0.309	0.372
Mean(dep. var.)	2.198				19.495			

5 Conclusion

Due to disagreements about how and when to implement policies about climate change, there is a large heterogeneity in these policies across the countries. This lack of coordination can create escape rooms and incentivize decisions to overcome the consequences of stricter policies. In this paper, we focus on banks and try to understand whether they exploit the heterogeneity in climate policies in their loan supply decisions. In particular, we use the syndicated loan market as a laboratory to study the link between the cross-border loan supply and the climate policy stringency of the banks' home countries.

We find that banks react to a more stringent climate policy at home by increasing their cross-border lending. Specifically, banks increase their shares in cross-border syndicated loans by 19.25 percent when the climate policy stringency of their home country increases by 35 stringency index points. To establish that the effect is not driven by loan demand, we use the granularity of syndicated loans and compare the banks within the same loan by employing loan fixed effects. To mitigate concerns about omitted variables, we instrument climate policy stringency with the time since a sample country has crossed the path towards industrialization, which we measure with GDP per capita crossing a USD 5,000 threshold. Economic theories argue that, as time passes, industrialized economies should have a better environmental performance over time (Grossman and Krueger, 1995), thus predicting a stricter government policy for climate-related issues. We empirically show that our instrument is relevant and creates plausibly exogenous variation in the domestic climate policy stringency of lender countries.

Why do we observe the increase in cross-border lending? Our findings are in line with a race to the bottom behavior, in which the increase in cross-border lending reduces banks' exposure to climate policies. For instance, the positive effect on cross-border lending decreases in the borrower country's policy stringency and is non-existent if the stringency is higher in the borrower country. In addition, domestic lending to brown borrowers decreases, but cross-border lending increases to such borrowers as climate policy becomes more stringent. We demonstrate a negative correlation between climate policy stringency and banks' loan portfolio performance as a possible explanation for why banks have incentives to increase their lending abroad.

Our paper has important implications for the existing lack of coordination in climate policies. Considering the nature of climate change, an action that reduces the pace of transition into a green economy can have far-reaching negative externality. By studying the previously overlooked use of cross-border lending, we aim to provide a broader picture of how international banking interacts with climate policies, which can help policymakers improve international coordination and develop more effective policies.

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Internet appendix

A Data description

A.1 Climate policy stringency and the CCPI

The Climate Change Performance Index (CCPI) has been internationally recognized for assessing a country's climate change performance index. Here are a few examples showing the index's impact:

- The Institutional Investor Group on Climate Change (IIGCC) has named the CCPI "recommended methodology" for climate-proofing sovereign bonds (link), and the CCPI presents countries' rankings at the COP to the UNFCCC (link);
- The European Parliament has ranked the CCPI "first" within their ten composite indices for policy-making (link);
- The G20's Financial Stability Board (FSB) has named the CCPI a proxy for transition risks as part of their research on the availability of data to assess climate-related risks to financial stability (link);
- The World Bank has referenced the CCPI as one of the three most robust key performance indicators for sovereign sustainability globally (link);
- BlackRock has undertaken major research of CCPI-adjusted smart-beta strategies making extensive use of the Germanwatch data, as part of their systemic research approach (link);
- NN Investment Partners, a subsidiary of Goldman Sachs, has published a statement on creating net-zero investment portfolios within sovereign bonds, referencing their use of the CCPI database (link).

A.2 Country characteristics

Due to the possible effect of country-level characteristics on cross-border lending and climate policy stringency, we collect information about countries' economic conditions, culture, demography, law, and quality of institutions from several sources (Worldwide Governance Indicator, The Heritage Foundation, Fraser Institute among others). The common language and distance dummy variables come from Rose (2004). We also measure countries' competition in the domestic banking sector as the share of the five largest banks in total bank deposits. Finally, to examine whether the quality of banking system regulation affects cross-border lending activity, we rely on Barth et al. (2013) data set and their measures of countries' stringency of bank regulation -capital regulation, independence of supervisory authority and power of supervisory authority indices.[i]

A.3 Carbon intensity measure

We gather borrower-level data on carbon intensity from Sustainalytics. Sustainalytics rates the sustainability of publicly-listed companies based on their social, environmental, and corporate performance. It offers a time-varying carbon risk rating based on carbon emissions for 4,000 companies from 2013 to 2017. The rating is an effort to assess the degree to which a company is exposed to unmanaged carbon risk, or the risks arising in the transition process to a low-carbon economy. We create the variable *high carbon intensity risk* as a dummy variable equal to 1 if the firm is assigned to a Severe, High, or Medium Carbon Risk Category according to the final overall firm's carbon risk rating score.[ii] We compile data for 1,419 firms, of which 72.5 percent are defined as at high carbon intensity risk.

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[i]The data set provides information on bank regulation, supervision, and monitoring in more than 100 countries. As the indices are not available annually, we follow the literature and use the value of the variables from the third survey (data as of 2005) for 2005 to 2010, and the value of the variables from the last survey for the period 2011 ongoing.

[ii]The Carbon Risk Rating score ranges in the interval [0;100]. The score band and assigned categories are organized as follows: 0.00 - Negligible Risk; 0.01-9.99 - Low Risk; 10-29.99 - Medium Risk; 30-49.99 - High Risk; $\geq$50 - Severe Risk.

Figure A1: **Variation in the climate policy stringency**

This figure reports the average value against the Climate Change Performance Index (CCPI) standard deviation for each country included in our sample. The CCPI score takes values in the interval [0;100], where higher values proxy a country with a more stringent climate policy. The panel consists of 39 countries over the period 2007-2017. Dots are colored according to the regional area where countries are located (Europe, Anglo-Saxon, Asia, and Emerging markets). The y-axis shows the standard deviation, while the x-axis shows the average value of the CCPI. For the list of the countries included in our sample, see Figure A3. For the variation in each CCPI component, see Figure A4.

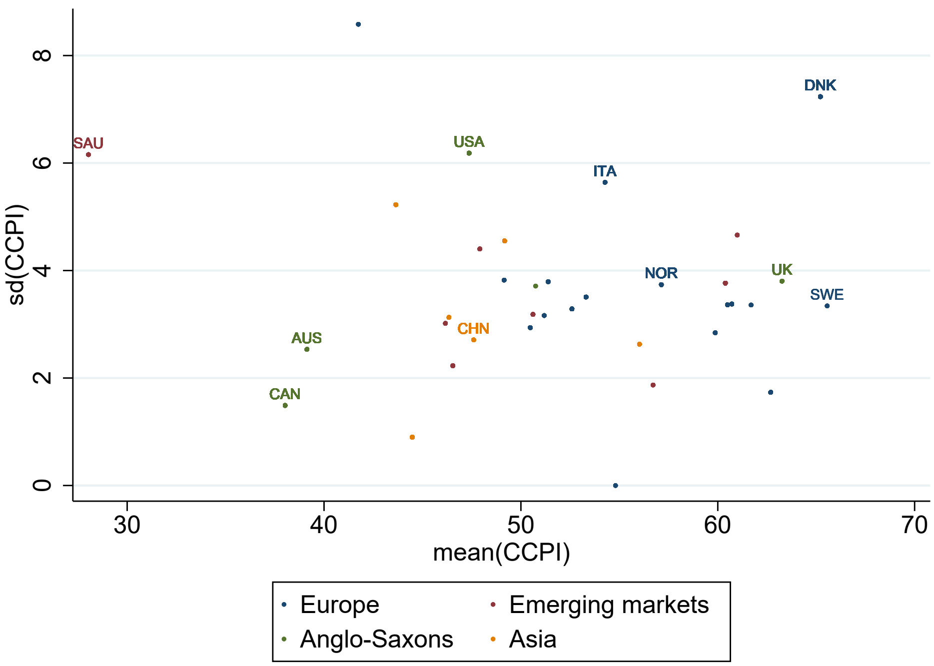
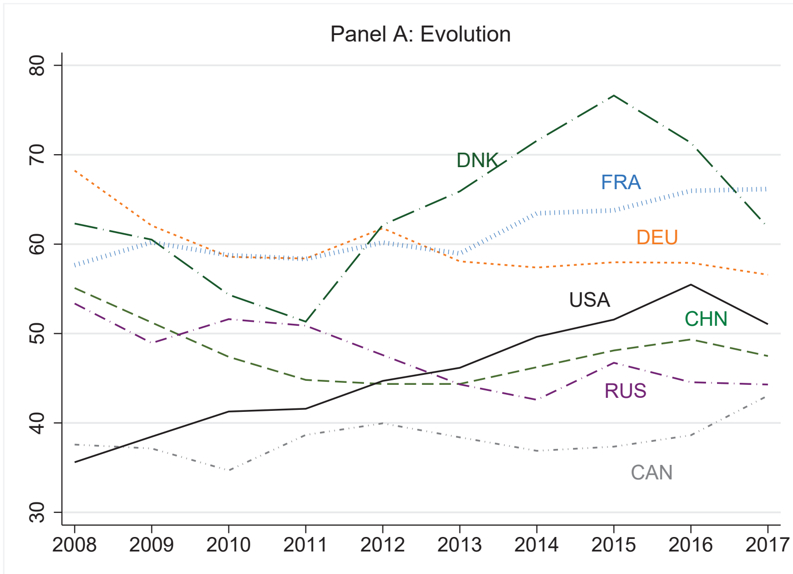


Figure A2: **Evolution over time and changes in climate policy stringency**

This figure shows the evolution and percentage change in the CCPI index over the period 2007-2017 for a sample of representative countries. The x-axis shows the sample period. In Panel A, the y-axis shows the CCPI values; in Panel B, the y-axis shows the change in the CCPI. For the list of the countries included in our sample, see Figure A3.



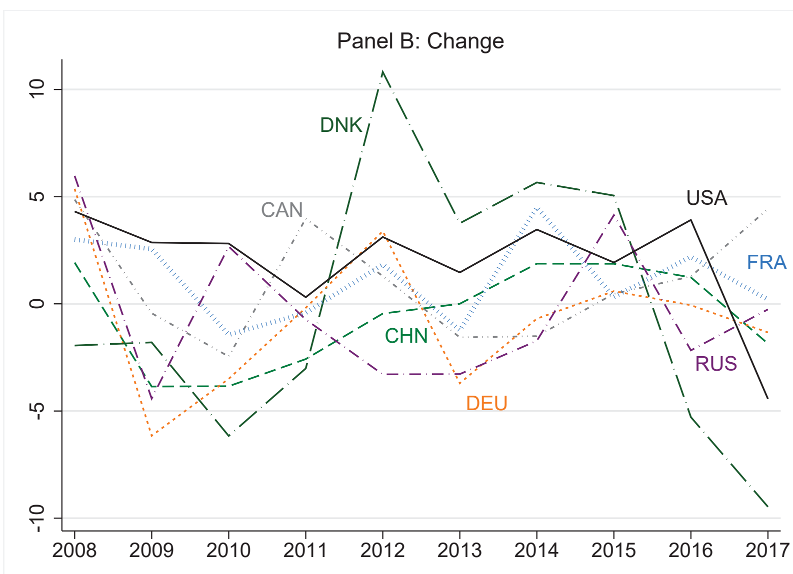
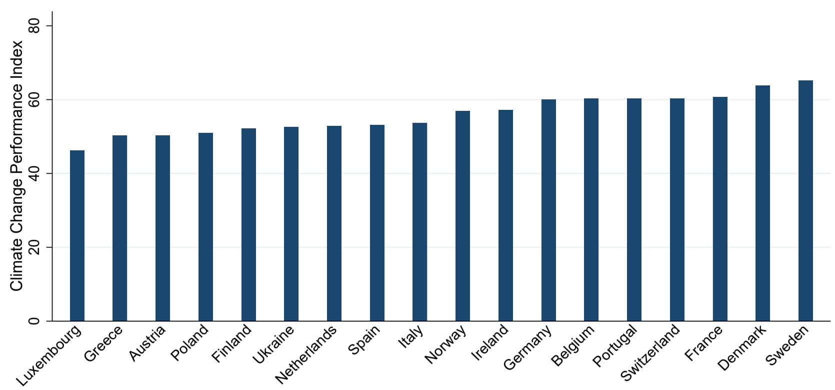


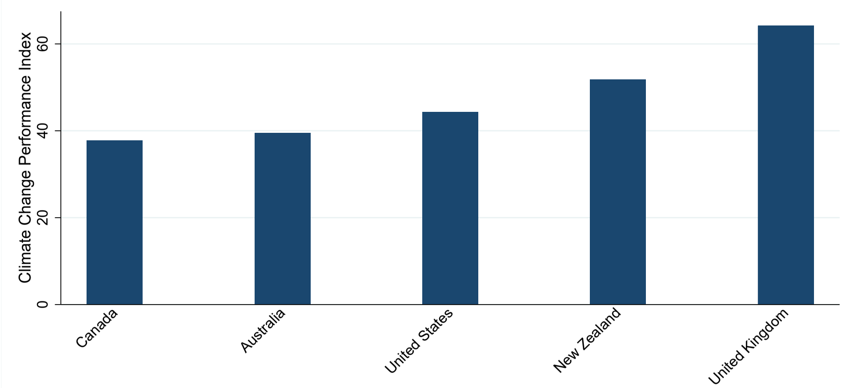
Figure A3: **Average home country climate policy**

This graph reports the average Climate Change Performance Index (CCPI) for each country included in our sample over the period 2007-2017.

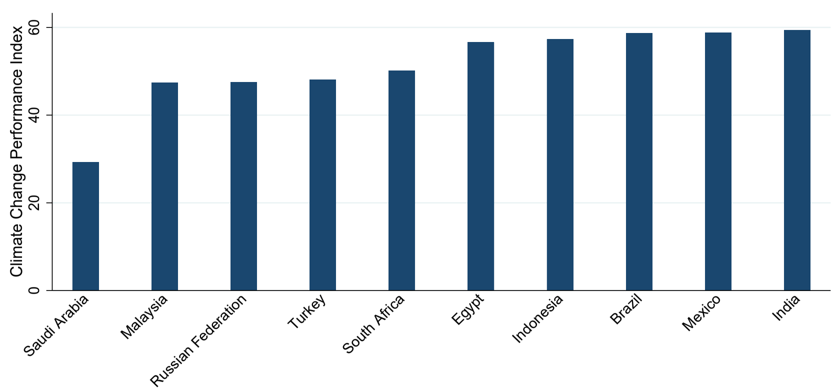
(a) Europe



(b) Anglo-Saxons



(c) Emerging markets



(d) Asia

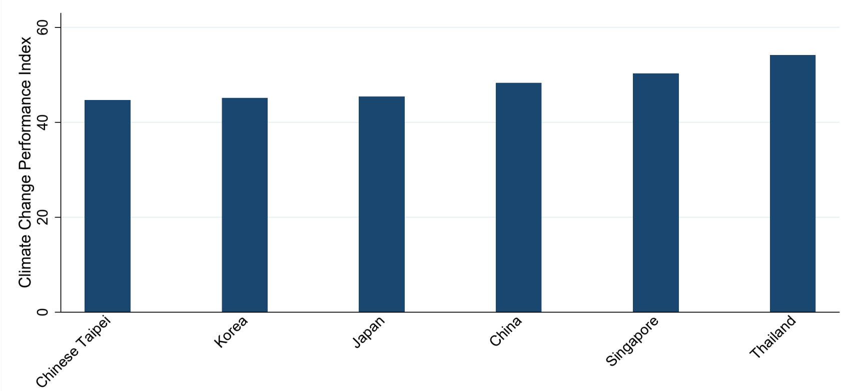


Figure A4: **Variation in CCPI components**

This figure reports the average value against the standard deviation of each component of the CCPI index and for each country included in our sample. The *GHG emissions* component's value range in the interval [0;60]. The *Climate policy* component's value range in the interval [0;20]. The *Renewable energy* component's value range in the interval [0;10]. The *Energy efficiency* component's value range in the interval [0;10]. The panel consists of 39 countries over the period 2007-2017

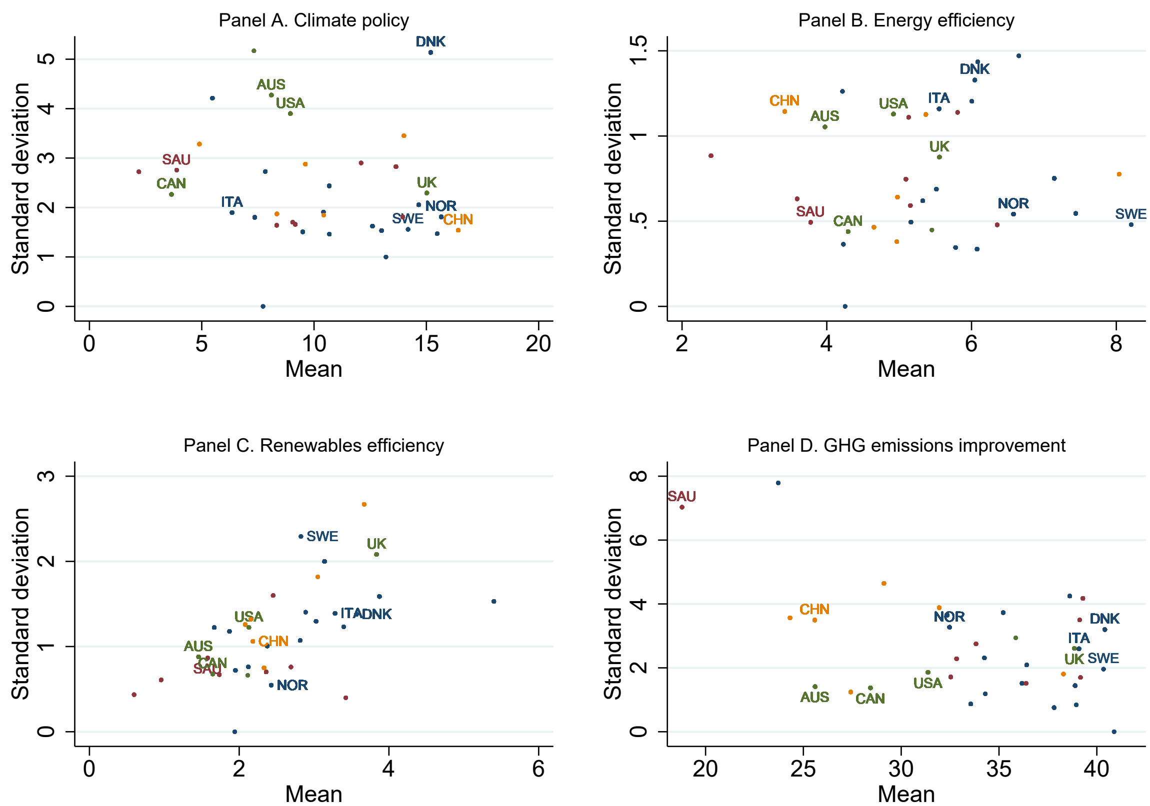


Figure A5: **Correlation between home country climate policy and cross-border bank lending**

This figure reports the correlation between the climate policy stringency measured by the Climate Change Performance Index (CCPI) and the share of cross-border lending in total lending on bank balance sheets. Share of cross-border lending is calculated as the ratio between the total cross-border loan volume that each parent bank in the sample has financed in the syndicated loan market over the period 2007-2017 and total net loans. For variable definitions, see Table A1.

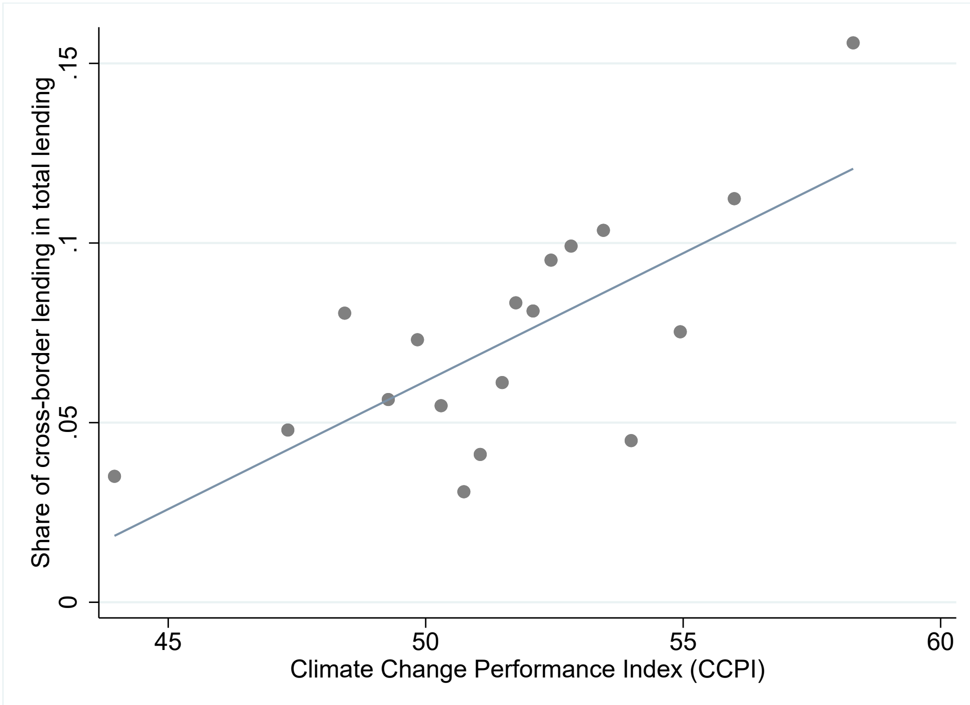


Figure A6: **The effects of climate policy stringency on cross-border lending: Main results**

These maps visually depict the main results of our analysis. Specifically, it shows three sample countries (United Kingdom, Brazil, and Australia) to represent the intuition and results from our study: Banks located in countries with stricter climate policy (e.g., UK) increase their cross-border lending to high carbon intensity risk firms (i.e., polluting firms) located abroad (e.g., in Brazil) compared to a similar bank that is located in a lax climate policy country (e.g., Australia) and that joins the syndicated loan granted to the same foreign firm.

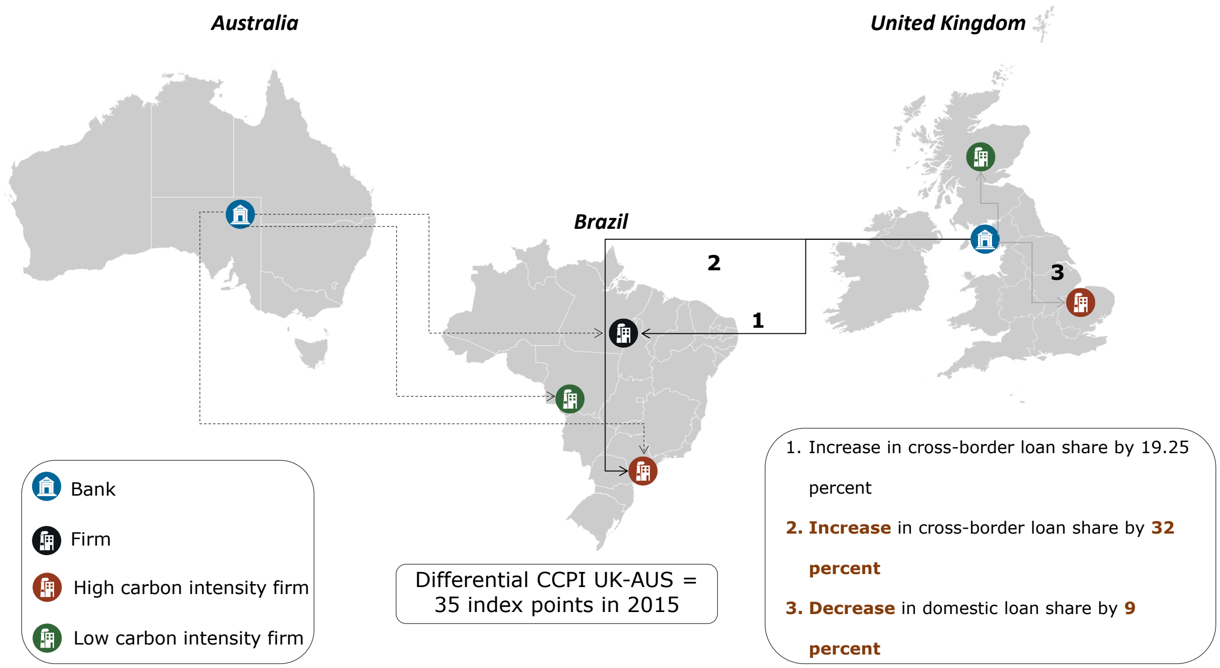


Figure A7: **Time since industrialization and the exclusion restriction**

This figure shows the estimated coefficient of $\mathrm{CCPI}_{\mathrm{lender}}$ when the exclusion restriction assumption is relaxed. The dashed lines on the y-axis are 90 percent upper and lower bounds for the estimated coefficient of $\mathrm{CCPI}_{\mathrm{lender}}$ with the method developed by Conley et al. (2012). The x-axis shows the direct effect of $ln(Years\ since\ GDP_{pc} > 5k)$ on cross-border lending after controlling for its effect through $\mathrm{CCPI}_{\mathrm{lender}}$ and country-level variables. For variable definitions, see Table A1.

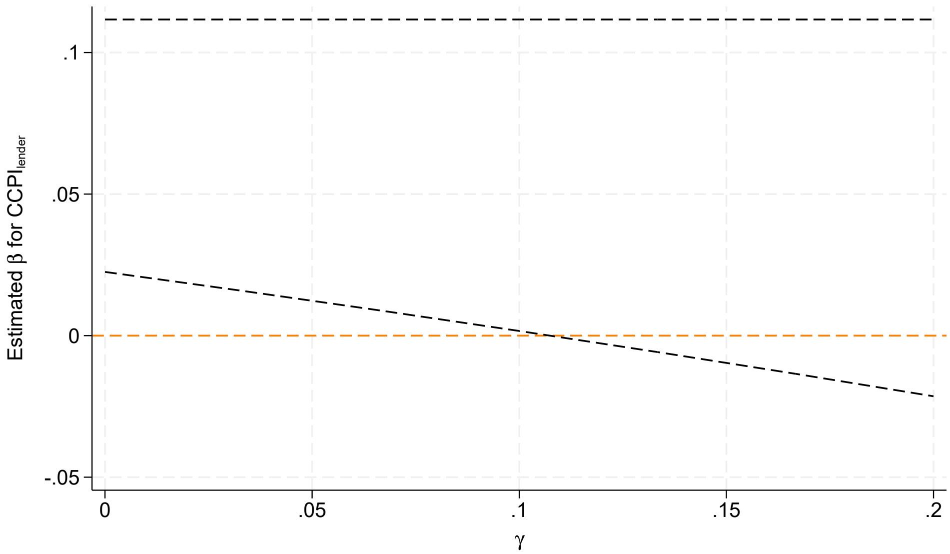


Figure A8: **Different time periods and the effect on cross-border lending**

This figure plots the coefficients of CCPI_{lender}, obtained from different time periods. The dependent variable is Lender Share. The models include loan fixed effects. The time periods are indicated on the x-axis. Bars indicate 90 percent confidence intervals. Standard errors are clustered at the lender's country-year level. For variable definitions, see Table A1.

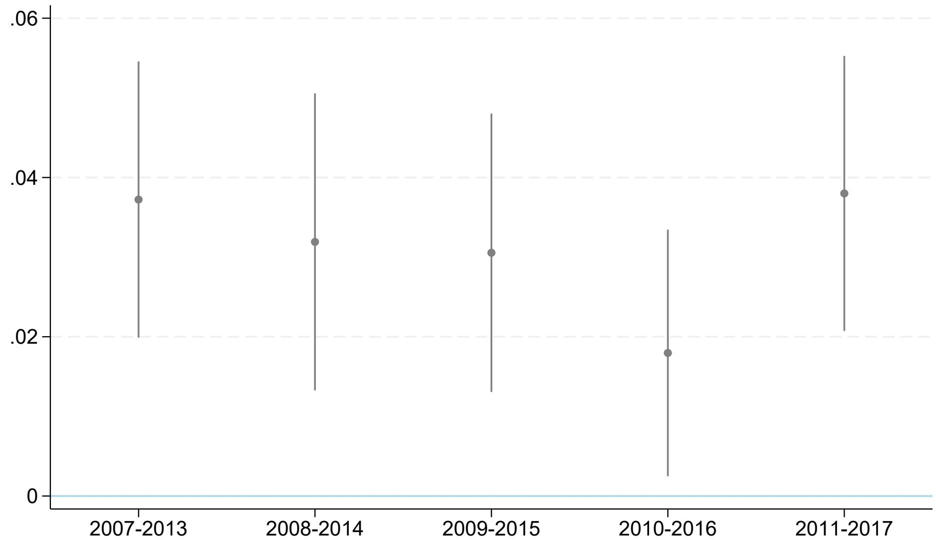


Table A1: **Variables description**

Variable name	Variable definition	Source
Lender share (%)	Cross-border loan share in % values financed by syndicated loan participants.	LPC's DealScan
CCPI	Country-level climate policy stringency proxied by the Climate Change Performance (CCPI). The score ranges from [0;100]	Germanwatch e.V.
Climate Policy	Country-level climate policy measuring government efforts in national and international climate policy. 20 percent of overall CCPI score. It ranges from [0;100].	Germanwatch e.V.
GHG Emissions	Country-level measure of GHG emissions. 60 percent of overall CCPI score. It ranges from [0;100].	Germanwatch e.V.
Renewable Energy	Country-level measure of usage of renewable energies. 10 percent of CCPI overall score. It ranges from [0;100]	Germanwatch e.V.
Energy Efficiency	Country-level measure of efficiency in energy usage. 10 percent of overall CCPI score. It ranges from [0;100].	Germanwatch e.V.
Total assets (log)	The natural logarithm of the value of total assets in USD millions.	Bankscope
Net Interest Margin (%)	Percentage of earnings in interest as compared to the outgoing expenditures payed to customers.	Bankscope
Customer deposits (log)	Total customer deposits in USD millions.	Bankscope
Nonperforming loans (NPL) (%)	Ratio of loans defined to be nonperforming over gross loans in USD millions.	Bankscope
Liquidity ratio (%)	Ratio of liquid assets over deposits and short-term funding.	Bankscope
GDP per capita (log)	Logarithm of gross domestic product divided by midyear population at the country-year level.	World Bank
GDP growth (%)	Annual GDP growth rate.	World Bank
Domestic credit to GDP (%)	Domestic credit to private sector as % of GDP at the country-year level.	World Bank
Unemployment rate (%)	Number people unemployed as a percentage of the labour force at the country-year level.	World Bank
Population growth rate (%)	Annual population growth rate calculated as the exponential rate of growth of midyear population from year t-1 to t. Population counts all residents regardless of legal status or citizenship.	World Bank
Old workforce (%)	Ratio of older dependents–people older than 64–to the working-age population–those ages 15-64.	World Bank
Young workforce (%)	Ratio of young dependents–people younger than 15–to the working-age population–those ages 15-64.	World Bank
Common Language	Dummy variable that is equal to one if the two countries share the same language or have a former colonial relation.	Rose (2004)

Table A1 (cont.): **Variables description**

Variable name	Variable definition	Source
Distance (log)	Log of geographic distance borrower-lender's country.	Rose (2004)
High Carbon Intensity Risk	Dummy variable equals to 1 if the company (borrower) is assigned to a High, Severe, or Medium Carbon Risk Category; 0 otherwise (Negligible or Low Carbon Risk Category). Specifically, based on the distribution of the carbon risk scores, each company is assigned to one of the five Carbon Risk Categories.	Sustainalytics
Property rights	Score that ranges from 0 to 100. Countries with more secure property rights and legal institutions that are more supportive of the rule of law receive higher ratings.	Fraser Institute Website (2008)
Number of days to enforce contracts (log)	The enforcing contracts indicator measures the time and cost for resolving a commercial dispute through a local first-instance court and the quality of judicial processes index. It counts the number of days the lawsuit filing in court until payment.	World Bank Doing Business Database
Strength of legal rights index	Strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders, facilitating lending. The index ranges from 0 to 12, with higher scores indicating that these laws are better designed to expand access to credit.	World Bank Doing Business Database
Top five bank concentration (all banks)	The fraction of total assets held by the five largest banks in the country.	World Bank Global Financial Development Database
Capital regulatory index	The sum of overall capital regulatory stringency and initial capital stringency, which measures whether certain funds may be used to initially capitalize a bank and whether they are officially verified. A higher value indicates greater stringency. We use the latest available observation of the same country if the data is missing.	Barth et al. (2013)
Independence of supervisory authority	The degree to which the supervisory authority is independent of the government and legally protected from the banking industry. The indicator is constructed based on the following three questions. (1) Are the supervisory bodies responsible to (a) the Prime Minister, (b) the Finance Minister or other senior government officials, or (c) a legislative body (yes = 1)? (2) Whether the supervisors can be sued if they take of the supervisory agency have a fixed term actions against a bank (No = 1)? (3) Does the chair value means a more independent supervisory contract and how long? (=1 if term $\geq$ 4). Higher values mean more independent supervisory authority. We use the latest available observation of the same country if the data is missing.	Barth et al. (2013)
Official supervisory power	An index aggregating supervisory power. Specifically, it indicates whether the supervisory agency has the legal right to meet directly with external auditors to discuss their report without getting approval from the bank; intervene in the ownership rights; or suspend the board decision to distribute dividends, among others.	Barth et al. (2013)
Years since GDP_{pc}>5k (log)	The logarithm of the time in years since a sample country's GDP per capita exceeds USD 5,000. GDP per capita is defined as Real GDP per capita in 2011 USD terms.	Maddison Project Database 2020 (Bolt and van Zanden, 2025)

Table A1 (cont.): **Variables description**

Variable name	Variable definition	Source
Same country	Dummy variable equal to 1 if the lender and the borrower are located in the same country; 0 otherwise This variable indicates a loan granted domestically.	LPC's DealScan
Loan amount	Log change in the amount of cross-border lending by bank i to destination country j. The variable is constructed as log(1+ the amount of cross-border lending).	LPC's DealScan
Number of loans	Log change in the number of cross-border loans by bank i to destination country j. The variable is constructed as log(1+ the number of cross-border lending).	LPC's DealScan
EPI	The EPI (The Environmental Policy Index) is a composite indicator that measures how countries address national environmental challenges. The EPI categories track performance and progress on two broad policy objectives: Environmental Health and Ecosystem vitality.	Hsu et al. (2016)
C3-I	The C3-I (The Climate Change Cooperation Index) measures countries' climate policy performance, both in terms of political behavior (output) and emissions (outcome).	Bernauer and Böhmelt (2013)
EPS	The OECD EPS (Environmental Policy Stringency) index is a country-specific and internationally comparable indicator of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting.	Kruse et al. (2022)

Table A2: **Cross-border lending by participants from countries other than the lead arrangers'**

This table reports estimates from Equation 1 but uses the sample of shares from participant banks in countries different from the lead arrangers'. The dependent variable is Lender share and the main independent variable is $\text{CCPI}_{\text{lender}}$. We identify participants and lead arranger(s) following Ivashina (2009). Moreover, for those loans with multiple lead arrangers, we identify the leading bank(s) by the highest loan share financed in the syndicated loan. Columns (1) to (5) report the results from Equation 1, mirroring our baseline evidence in Table 2. Columns (6) and (7) split the sample into two with respect to whether the sample loans have a lead arranger or not. The sample covers the period 2007-2017. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Participant Share	Baseline					Has lead arranger	
	(1)	(2)	(3)	(4)	(5)	(6) Yes	(7) No
$\text{CCPI}_{\text{lender}}$	0.034*	0.045***	0.045***	0.045***	0.042***	0.044***	0.042***
	(0.019)	(0.009)	(0.009)	(0.008)	(0.008)	(0.015)	(0.008)
Bank Group Controls	✓	✓	✓	✓	✓	✓	✓
Borrower FE		✓	✓				
Year FE			✓				
Borrower × Year FE				✓			
Loan FE					✓	✓	✓
Obs.	10,870	10,834	10,834	10,797	10,742	1,158	9,584
R^2	0.005	0.747	0.749	0.820	0.851	0.682	0.858
Mean(Lender Share)	7.447						

Table A3: **Green Party share as an instrument for climate policy stringency**

This table reports estimates from Equation 1 in which CCPI is instrumented by ΔGreen Party Share. The dependent variable is Lender Share. The sample covers the period 2007-2017 and includes only European lenders. Column (1) reports the first stage. Column (2) includes loan fixed effects. Column (3) includes the Green Party's other policies, measured by the Manifesto Project (Lehmann et al., 2023). Column (4) includes country controls. 1^{st} Stage Efficient F-statistics are calculated by the method developed by Olea and Pflueger (2013). The Green Party's other policies are about the economy, international relations, social policies, and welfare policies. Country control variables are GDP per capita, GDP growth, domestic credit to GDP ratio, unemployment rate, change in government expense to GDP ratio, and change in trade openness ((imports+exports)/GDP). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	$\text{CCPI}_{\text{lender}}$	Lender Share		
	(1)	(2)	(3)	(4)
ΔGreen Party Share	1.600***			
	(0.342)			
$\widehat{CCPI}_{\text{lender}}$		0.122***	0.122*	0.135**
		(0.040)	(0.067)	(0.063)
GP's other policies			✓	✓
Country Controls				✓
Loan FE	✓	✓	✓	✓
Obs.	3,572	3,572	3,572	3,557
R^2	0.695	0.020	0.026	0.033
1^{st} Stage Eff. F-stat		17.578	19.817	19.695
Mean(Lender Share)	7.942			

Table A4: **Climate policy stringency and firm profits**

This table documents the negative correlation between climate policy stringency and firm profits. The sample covers the period 2013-2017. Column (1) uses Return on Equity as the dependent variable. Column (2) uses Return on Capital as the dependent variable. Column (3) uses the Net Profit Margin as the dependent variable. Column (4) uses the Operating margin as the dependent variable. Control variables and fixed effects are indicated at the bottom of each column. Control variables are country-level population growth, ratio of the young workforce, GDP growth, unemployment rate, monetary policy rate, GDP per capita, and domestic credit to GDP ratio. Robust standard errors are shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	ROE	ROC	Net Margin	Opr. Margin
	(1)	(2)	(3)	(4)
CCPI	-0.007**	-0.004*	-0.007**	-0.004*
	(0.003)	(0.002)	(0.003)	(0.002)
Controls	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Obs.	214	213	216	216
R^2	0.302	0.291	0.337	0.395
Mean(Dep. var.)	0.096	0.079	0.076	0.097

Table A5: **Climate policy stringency exposure from lenders and carbon emissions**

This table investigates the relationship between exposure to climate policy stringency via the lenders and the borrowers' carbon emissions. The dependent variable is the log of carbon emissions divided by total revenue. The main independent variable is CCPI exposure, which is a weighted average of lenders' CCPI where the weights are loan amounts. Column (1) uses the contemporaneous $ln(Carbon\,em./Tot.\,revenue)$. Column (2) uses $ln(Carbon\,em./Tot.\,revenue)$ one year later. Column (3) uses $ln(Carbon\,em./Tot.\,revenue)$ two years later. Fixed effects are indicated at the bottom of each column. Standard errors are robust and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	ln(Carbon em./Tot. revenue)		
	(1)	(2)	(3)
	t=0	t=1	t=2
CCPI exposure	0.008	0.022	-0.024
	(0.016)	(0.015)	(0.044)
Borrower FE	✓	✓	✓
Obs.	253	201	153
R^2	0.980	0.992	0.991
Mean(Dep. Var.)	4.738		

Table A6: **The role of domestic borrowers in race to the bottom mechanism**

This table reports estimates from Equation 1. The dependent variable is subsidiary lending, and the main independent variable is $\text{CCPI}_{\text{lender}}$. Subsidiary lending is a dummy variable that takes the value of one when the bank has a lending relationship with the parent company of the cross-border borrower in the bank's home country. The sample covers the period 2007-2017. Control variables and fixed effects are indicated at the bottom of each column. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Subsidiary Lending		
	(1)	(2)	(3)
$\text{CCPI}_{\text{lender}}$	0.0003*	0.0004**	0.0003
	(0.0002)	(0.0002)	(0.0002)
Bank Group Controls		✓	✓
Country Controls			✓
Loan FE	✓	✓	✓
Obs.	11,671	11,671	10,776
R^2	0.925	0.925	0.934
Mean(Dep. Var.)	0.113		

Table A7: **Climate policy component and cross-border lending**

This table reports estimates from Equation 1. The dependent variable is Lender share and the main independent variable is CCPI's Climate policy$_{\text{lender}}$. The sample covers the period 2007-2017. All regressions include lagged bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1, + p<0.101.

	Lender Share				
	(1)	(2)	(3)	(4)	(5)
Climate policy$_{lender}$	0.060*	0.059***	0.059***	0.062***	0.057***
	(0.033)	(0.013)	(0.012)	(0.012)	(0.012)
Bank Group Controls	✓	✓	✓	✓	✓
Borrower FE		✓	✓		
Year FE			✓		
Borrower × Year FE				✓	
Loan FE					✓
Obs.	11,671	11,671	11,671	11,671	11,671
R^2	0.005	0.739	0.741	0.811	0.843
Mean(Lender Share)	7.595				

Table A8: **Climate policy stringency and loan terms**

This table reports estimates from Equation 1 and interacts $CCPI_{lender}$ with loan terms. Maturity is measured in months. Spread is in basis points. Covenant is a dummy variable that takes the value of one if there is a financial covenant. The sample covers the period 2007-2017. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share		
	(1)	(2)	(3)
$CCPI_{lender}$ × spread	0.000		
	(0.000)		
$CCPI_{lender}$ × log(Maturity)		-0.006	
		(0.008)	
$CCPI_{lender}$ × covenants			0.004
			(0.011)
$CCPI_{lender}$	0.048***	0.042***	0.041***
	(0.010)	(0.008)	(0.009)
Bank Group Controls	✓	✓	✓
Loan FE	✓	✓	✓
Obs.	8,915	11,601	11,671
R^2	0.807	0.843	0.844
Mean(Lender Share)	7.595		

Table A9: **The effect of home country climate policy stringency on cross-border lending (2007-2023)**

This table reports estimates from Equation 1 but on an extended sample period (2007-2023). The dependent variable is Lender share and the main independent variable is $CCPI_{lender}$. Fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share			
	(1)	(2)	(3)	(4)
$CCPI_{lender}$	0.044***	0.064***	0.050***	0.039***
	(0.011)	(0.011)	(0.009)	(0.009)
Borrower FE	✓	✓		
Year FE		✓		
Borrower × Year FE			✓	
Loan FE				✓
Obs.	17,003	17,003	16,997	17,007
R^2	0.741	0.746	0.789	0.812
Mean(Lender Share)	9.892			

Table A10: **Home country climate policy and cross-border loan amounts**

This table reports estimates from Equation 1. The dependent variable is log(loan amount) and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	log(Loan amount)				
	(1)	(2)	(3)	(4)	(5)
$CCPI_{lender}$	0.030***	0.012***	0.012***	0.013***	0.012***
	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
Bank Group Controls	✓	✓	✓	✓	✓
Borrower FE		✓	✓		
Year FE			✓		
Borrower × Year FE				✓	
Loan FE					✓
Obs.	11,671	11,671	11,671	11,671	11,671
R^2	0.070	0.738	0.741	0.808	0.903
Mean(log(Loan amount))	17.374				

Table A11: **Imputing the missing loan share**

This table reports estimates from Equation 1 when we impute the missing loan shares. The dependent variable is Lender share and the main independent variable is $\text{CCPI}_{\text{lender}}$. The sample covers the period 2007-2017. All regressions include bank group level controls (net interest margin, Tier 1 capital ratio, log(total assets), log(customer deposits), and liquidity ratio). Control variables and fixed effects are indicated at the bottom of each column. Standard errors are clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share			
	(1)	(2)	(3)	(4)
$\text{CCPI}_{\text{lender}}$	0.038***	0.040***	0.030***	0.020***
	(0.014)	(0.011)	(0.006)	(0.006)
Bank Group Controls	✓	✓	✓	✓
Borrower FE	✓	✓		
Year FE		✓		
Borrower × Year FE			✓	
Loan FE				✓
Obs.	38,634	38,634	38,634	38,634
R^2	0.585	0.588	0.847	0.916
Mean(Lender Share)	16.734			