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

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JEL Classification: G21, H73, Q58

Keywords: Cross-border lending, Climate Policy, regulatory arbitrage, syndicated loans

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1 Introduction

Climate change is a global problem whose solution needs global coordination and cooperation.[1] Despite this need, there is still significant heterogeneity across countries regarding climate policy stringency.[2] This heterogeneity may allow the firms to circumvent the higher climate policy stringency in their home country by shifting their operations to less-stringent countries, which can undermine the efforts to combat climate change.[3] In a similar fashion, higher stringency can also affect bank behavior due to its possible adverse effects on the loan portfolio.

In this paper, we focus on cross-border lending and investigate whether banks use cross-border lending to react to a change in climate policy stringency in their home country. To investigate cross-border lending, we use a sample of syndicated loans for the years between 2007 and 2017, where lenders are located in 42 different countries and borrowers are located in 40 different countries. We find that banks react to higher climate policy stringency in their home country by increasing their cross-border lending. Specifically, a one standard deviation higher climate policy stringency results in an average increase in the cross-border loan share of approximately almost one percentage point (pp), corresponding to a nine percent increase relative to the mean loan share. To put these numbers in perspective, we can consider a hypothetical example of a cross-border syndicated loan where one lender is located in Germany, the other lender is in the U.S., and the borrower is in a third country, say, Poland. Our results indicate that Germany's six index points stringent climate policy in 2015 leads the bank in Germany to have a 6 percent higher loan share in this loan compared to the bank in the U.S. We show that the increase in cross-border lending is not driven by loan

[1] In the July 20th, 2022, "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)."

[2] For instance, Germany has introduced financial aid to support research on technologies for decarbonizing heavy industry (link). In contrast, the Build Back Better Act could not get enough support to pass the U.S. Senate, partly due to the provisions it will introduce related to climate change (link).

[3] Bartram et al. (2021), for example, document that financially constrained firms shift emissions and output from California to other states after the introduction of the cap-and-trade program.

demand by using loan fixed effects to control for loan demand. Moreover, we dispel concerns about omitted variables by instrumenting climate policy stringency with the Green Party shares in the domestic parliament.

Our results are in line with banks using cross-border lending as a regulatory arbitrage tool. We find that cross-border lending decreases in borrower's climate policy stringency and occurs only if the lender's country has a more stringent climate policy than the borrower's country. Furthermore, if the borrower has a high carbon intensity risk, climate policy stringency decreases domestic lending while it increases cross-border lending. We also find that climate policy stringency is negatively correlated with firm profits, providing suggestive evidence for the decline in domestic lending. Overall, our results depict a clear picture in which banks use cross-border lending as a regulatory arbitrage tool against climate policies, which may reduce the effectiveness of these policies.

Our measure of climate policy stringency is Climate Change Performance Index (CCPI).[4] Being a popular index among both academicians and practitioners, CCPI comes with two main advantages (Atanasova and Schwartz, 2019; Delis et al., 2019). First, a weighted average of 14 different climate policy indicators, CCPI is a broad and inclusive assessment of climate policy stringency. Second, it facilitates climate policy comparison among countries with different backgrounds as it summarizes the differences with one metric. We combine CCPI with syndicated loan data, 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, a combination of CCPI and syndicated loan data provides a relevant setting to investigate whether banks alter their cross-border lending to react to a change in climate policy stringency.

[4]CCPI is developed by Germanwatch with the aim to track efforts to combat climate change in 57 countries and the European Union (Burck et al., 2016). We provide more details on CCPI in Section 2.

A naive regression model in which cross-border lending is regressed on CCPI can suffer from two primary sources of endogeneity. The first one is about loan demand. Observing an increase in CCPI of a country, a borrower may increase its loan demand to the lenders from that country. One reason can be that the borrower can use a relationship with a lender from a high CCPI country as a signaling device. Alternatively, the borrower may want to increase its knowledge in efforts against climate change, and a lending relationship with this lender can provide this knowledge. These arguments imply that the relationship between CCPI and cross-border lending cannot be interpreted in terms of the loan supply without properly controlling for loan demand. We use the granularity of the syndicated loan data and control for loan demand with loan fixed effects. Loan fixed effects provide a comprehensive approach to control for loan demand in a syndicated loan sample, thanks to the institutional setting of syndicated loans. In a syndicated loan, except for the lead arranger, lenders have limited interactions with the borrower. This lack of interaction suggests that comparing the lenders within the same loan highly likely holds loan demand constant. This, in turn, enables us to identify the credit supply effects of climate policy stringency.[5]

A second concern about the naive model is that there can be other country level characteristics that are correlated both with CCPI and cross-border lending, which would induce omitted variable bias. For instance, an improvement in economic conditions can lead to an increase in both CCPI and cross-border lending. Or, a change in demographics of the country can affect CCPI by altering the perception of the climate change and cross-border lending by affecting loan demand. We show that controlling for factors that are found to be related to cross-border lending in the literature does not change the positive effect of climate policy stringency on cross-border lending. Despite this robustness, there can be unobservable variables that still induce omitted variable bias, which entails an exogenous variation in climate policy stringency.

[5] We also show that exposure to lenders' CCPI does not have an impact on carbon emissions at the borrower level, which provides additional support for the loan supply channel.

We obtain this exogenous variation by using the Green Party share in the parliament as an instrument for climate policy stringency. The Green Party share is a credible instrument in our setting for two main reasons. First, thanks to the focus of these parties on environmental problems, the Green Party share is correlated with countries' climate policy stringency. Second, given that these shares change only after the elections, which occur in predetermined electoral cycles, the Green Party share is likely to satisfy the exclusion restriction. We provide evidence for the validity of this assumption by documenting that these shares are not correlated with economic conditions − the most probable threat to the exclusion restriction. Furthermore, we relax the exact exclusion restriction with the method developed by Conley et al. (2012). This method demonstrates that the magnitude of the direct effect of Green Party share on cross-border lending should be as large as the size of its effect through climate policy stringency. We find this implausible considering the lack of correlation between the Green Party share and economic conditions.

After establishing the positive effect of climate policy stringency on cross-border lending, we investigate the underlying mechanism. Our findings indicate that lenders use cross-border lending as a regulatory arbitrage tool to react to climate policy stringency. Regulatory arbitrage refers to lenders' actions to reduce the influence of changes in regulations on their loan portfolios (Nouy, 2017).[6] Thus, regulatory arbitrage predicts that the adjustment in cross-border lending should curtail lenders' exposure to climate policy stringency. In line with this prediction, we find that the positive effect of climate policy stringency on cross-border lending decreases as borrowers' climate policy gets more stringent. Moreover, regulatory arbitrage suggests that lenders should only increase their cross-border lending to reduce their exposure to climate policies if the borrower is subject to a less stringent climate policy. We find that, indeed, this is the case. The positive effect of climate policy stringency is highly statistically significant if the borrower has lower climate policy stringency. However, the effect on cross-border lending is absent if the borrower's climate policy stringency is

[6] Carruthers and Lamoreaux (2016) survey the literature on regulatory arbitrage.

higher than that of the lender. Another regulatory arbitrage prediction is about the lender country's banking supervision environment. In countries where bank supervision power is low, exploiting regulatory arbitrage can be easier for lenders since supervisors are less likely to take action against regulatory arbitrage. By splitting the sample in terms of bank supervision power, we show that the effect is larger for such countries, which provides additional evidence for the mechanism.

In addition, regulatory arbitrage also suggests that higher climate policy stringency may hinder lending to domestic borrowers with high carbon risk, which may encourage lenders to increase their cross-border lending to 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. Consistent with regulatory arbitrage, climate policy stringency reduces domestic lending to borrowers with high carbon risk. At the same time, it increases cross-border lending to borrowers with high carbon risk. We consider firm profitability as a reason for the decline in domestic lending. By requiring investment and changes in business models, a stringent climate policy can be negatively associated with firm profits. Four different measures of firm profitability confirm this negative association, implying that lower firm profits at home can be the driving force for the impact on cross-border lending.[7] As the last evidence for the underlying mechanism, we document that Climate Policy part of CCPI is the most crucial component for our results, compared to Greenhouse Gas Emissions, Renewable Energy, and Energy Use.

We start the last part of the paper by exploiting the heterogeneity among the lenders and borrowers. Exercises on lender-level heterogeneity show that lenders that are 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 lenders that have higher cross-border loans in their books and for lenders that face a higher nonperforming loans ratio (NPL). A higher cross-border loan ratio implies that

[7] These four variables are Return on Equity, Return on Capital, Net Profit Margin, and Operating Margin.

the lender has more experience with cross-border lending, which means that it is easier for this lender to use cross-border lending to react to changes in domestic climate policy stringency. Moreover, a higher NPL ratio creates a stronger incentive for the lender to engage with cross-border lending since a more stringent climate policy can reduce the returns of the loans when the lender needs a higher return rate due to the high NPL ratio. In terms of geographical heterogeneity among borrowers, we focus on European lenders and find that European lenders increase their cross-border lending more to borrowers in emerging market countries. At the same time, the effect is insignificant if the borrowers are located in Europe. Lastly, we consider different specifications in the appendix of the paper. We first use loan amounts, instead of loan shares as the dependent variable in loan level regressions. Second, we aggregate the loan level data up to the borrower country level and use the number of loans and loan amounts as dependent variables. In these specifications, we again estimate a positive and significant effect for climate policy stringency.

Our paper mainly contributes to the literature on climate change and finance. First, our paper is related to the discussions about 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).[8] Due to this challenge, firms may prefer to reallocate their activities to the areas with less stringent climate policies (Bartram et al., 2021).[9] 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

[8] 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, 2017). Investors may demand higher returns considering these risks (Chava, 2014; Painter, 2020; Bolton and Kacperczyk, 2021; Hsu et al., 2022; Nguyen et al., 2022).

[9] Bartram et al. (2021) 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)

to borrowers in countries with less stringent countries as a reaction 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, 2018; Beyene et al., 2021), they reflect the climate risk on loan terms (Atanasova and Schwartz, 2019; Correa et al., 2020; Bolton and Kacperczyk, 2021; Delis et al., 2021; Mueller and Sfrappini, 2021; Ivanov et al., 2021). In addition, banks lower their loan supply to browner firms after committing themselves to carbon neutrality (Kacperczyk and Peydro, 2021).[10] We complement these 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 (Karolyi and Taboada, 2015), and regulatory arbitrage opportunities (Houston et al., 2012; Ongena et al., 2013; Demyanyk and Loutskina, 2016; Beck et al., 2022) 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 (2021) show that the incidence of carbon taxes can influence

[10] Degryse et al. (2021) show that environmentally conscious banks offer cheaper loans to green firms after the Paris Agreement.

the reallocation of fossil lending across the borders. Our paper complements the existing literature by documenting that heterogeneity in climate policy stringency among countries can also induce cross-border lending due to the regulatory arbitrage opportunities it creates. To do so, we use loan fixed effects to control for loan demand, which enables us to estimate loan supply in a clean way.

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

We combine several data sets to analyze if climate policy stringency affects cross-border lending. This section describes these data sets and the construction of the variables. We provide the summary statistics in Table 1 and definitions in Table A4 of the Appendix.

Bank loans We use syndicated loan data from LPC DealScan database to study cross-border lending. DealScan includes comprehensive loan-deal information on a global level. We use this data to gather information about loans, such as lenders' share, loan amount, loan origination date, names and locations of borrowers and lenders, among other characteristics. Loans can be provided in different currencies, however we transform all loans as denominated in USD. We restrict the analysis to the sample of loans originated between 2007 and 2017 due to availability of climate policy data. We focus on loans to non-financial firms by commercial, savings, cooperative, and investment banks.[11]

The dependent variable of our analysis is *Lender share*, which is the share of a lender in

[11]For lender's choice, we follow Doerr and Schaz (2021) and consider as a bank all lenders defined in DealScan as Commercial Banks, Finance Companies, Investment banks, Mortgage Banks, Thrift/S&L, and Trust Companies. For borrowers, we follow the literature and exclude borrowers with SIC code between 6000 and 6999 from the sample.

cross-border syndicated loans. We define a loan as cross-border if the lender and borrower are located in different countries. We use only reported loan shares without imputing for the missing observations.[12] The average value of cross-border loans' share is 7.72 percent with a standard deviation of 7.98.

Climate policy stringency We measure climate policy stringency by Climate Change Performance Index (CCPI). CCPI is an index developed by Germanwatch, a non-governmental environmental and development organization. The purpose of CCPI is to enhance transparency in countries' climate protection action (Burck et al., 2016).[13] The index, which is published anually, covers 57 countries and the European Union and takes values between 0 and 100, where a higher value corresponds to a more stringent climate policy.[14] The index is constructed by using fifteen measures with four main categories. These categories are Greenhouse Gas (GHG) Emissions (60 percent), Renewable Energy (10 percent), Energy Efficiency (10 percent), and Climate Policy (20 percent). GHG Emission considers countries' emission levels, and Renewable Energy assesses the share of renewable energies used by a country to achieve an effective emission reduction. Energy Use measures the reduction of energy use needed for products and services. The Climate Policy category is based on assessments made by 300 experts and non-governmental organizations, and it considers the measures taken by national governments to reduce greenhouse gases.[15] Since CCPI considers both the measures and effectiveness of measures and provides comparability across countries, it is a convenient index for country-level climate policy stringency (Delis et al., 2019; Atanasova and Schwartz,

[12] This is available for 28 percent of the sample in the period 2007-2017. We also remove observations with incorrect values, such as total loan shares larger than 100 or loan shares equal to 0.

[13] Germanwatch e.V publishes the index in collaboration with the NewClimate Institute and the Climate Action Network. The index is available starting from 2005 onwards. The updated version is presented annually at the UN Climate Change Conference.

[14] Publicly available CCPI includes changes in the methodology applied by Germanwatch from 2013 onward. From the Germanwatch, we received a CCPI data set based on a uniform weighting for each index component.

[15] Climate Policy category results from a research study conducted by researchers and organizations that are not (in any way) connected to their national governments. This aspect of independence makes this category unique.

2019; Lin et al., 2020; Beyene et al., 2021).

Figure 1 shows how climate policy stringency has changed between 2007 and 2017. This figure shows a general improvement in climate policy stringency, which varies across the countries. For instance, in Figure 2, we see that, within our sample, there is important heterogeneity in the amount of variation in CCPI. The average CCPI in our sample is 55.7, with a standard deviation of 8.17.

Electoral outcomes We collect data on national-level election outcomes from countries National Archives Election results. Specifically, we collect data on the total number of seats won by a given political party during the election year. We use this data to create the variable *Green Party share* as the share of won seats assigned to the national green party over the total number of seats in the Parliament. Because of elections do not take place annually, we assign this value to all years subsequent to a given election year -when national elections do not take place. Furthermore, because of Green parties do not always appear as registered national parties, or simply they do not run for national elections, we gather data on European countries only.[16] Our instrumental variable Δ *Green Party share* is equal to the change in Green party share of won seats in two subsequent election years.

Bank balance sheets We collect bank balance sheet data from Bankscope and BankFocus.[17] Due to lack of common identifiers, we hand-match banks in DealScan with financial information in Bankscope and BankFocus by bank name and country at consolidated level.[18] Prior to this match, we process bank names in DealScan to account for name changes, merg-

[16]We collect electoral data for the following countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

[17]The provider Bureau van Dijk has changed the name of the database Bankscope to BankFocus starting from the year 2017. BankFocus contains data from the year 2011. We merge the two sources of bank-level data and respective bank identifiers to have the complete data set on bank-level characteristics starting from 2006. In cleaning and arranging our Bankscope-BankFocus data set, we follow Duprey and Lé (2016).

[18]We consider consolidated status of mother bank integrating the statements of its controlled subsidiaries or branches. We employ a fuzzy match exercise, or probabilistic record linkage in Stata (Wasi and Flaaen, 2015).

ers, and acquisitions over the sample period. We link subsidiaries and branches to their parent financials. Indeed, as the amounts involved in a syndicated loan are too large for a subsidiary's balance sheet, funds are usually provided by the bank's headquarter (De Haas and Van Horen, 2013). However, subsidiaries are often involved by providing the parent bank with local information (De Haas and Van Horen, 2013).

Our data comprises a full set of bank balance sheet information on profitability, bank performance and financial health, bank type (controlled subsidiary, global ultimate owner, and other), business model, and detailed information on the location (country, state, address, postal code). Due to the availability of actual shares as reported in DealScan, our final sample of matched banks includes a total of 399 banks of which 276 are parent banks located in 32 countries. We identify the location of our sample banks using the country provided in the Bankscope-BankFocus data set. We finally match the bank-level data set to the climate policy stringency data using the country where each bank is located.

We measure bank's profitability by using return on average equity (ROAE) and net interest margins (NIM), customer deposits, and liquidity ratio for bank performance and financial health. Other bank variables include bank capital (Tier 1 Capital ratio) and size (log-total assets).

Firms' location We identify firms' location using Compustat/WRDS data. We match borrowers in the DealScan loan-level sample to Compustat North America and Global databases.[19] Compustat database provides details both on the country where the company's headquarter is located and the country where the company is legally registered. We use the former as a criterion to identify the borrower's country.[20] Our sample includes a total of 1,387 firms located in 40 countries.

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[19] We use the DealScan-Compustat link table to match DealScan and Compustat borrower's identifiers provided by Chava and Roberts (2008). The link table can be accessed through the following link: `http://finance.wharton.upenn.edu/~mrrobert/styled-9/styled-12/index.html`.

[20] A company may be registered in a different country from the one where it is actually conducting its business operations due to fiscal related reasons.

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 of 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.[21]

Carbon intensity measure In order to pin down the economic mechanism at a play, 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 over the period 2013-2017 to assess the degree to which a company is exposed to unmanaged carbon risk, or the risk driven by the transition 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.[22] We compile data for 1,419 firms of which 72.5 percent are defined as at high carbon intensity risk.

[21]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 the period 2005 to 2010, and the value of the variables from the last survey for the period 2011 ongoing.

[22]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.

3 Empirical strategy

Our objective is to estimate the causal effect of the home country's climate policy stringency on cross-border lending. To achieve this objective, we need to address two main identification challenges. The first one is about loan demand. A change in a country's climate policy stringency can alter the loan demand to its banks from abroad. This can occur if a firm deems country-level climate policy stringency as an indicator for the lending practices of banks from that country. The second challenge is that an omitted variable can affect both the climate policy stringency and cross-border lending. For instance, a change in a country's macroeconomic conditions can influence both the climate policy stringency and cross-border lending. These two challenges suggest that our empirical strategy needs to properly control for loan demand 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 causally identify the effect of climate policy stringency on cross-border lending. The reason is that a change in climate policy stringency can alter how banks screen and monitor their borrowers. For instance, banks may be more careful about their borrowers' environmental footprint due to a stricter climate policy. Therefore, firms that need to improve their environmental profile might shift their loan demand towards banks from countries with stricter policies to benefit from such banks' expertise. 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 use loan fixed effects. The use of granular 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 (Khwaja and Mian, 2008). 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. In a syndicated loan, typically, the lead arranger is the one that negotiates the loan amount and other terms with the firm. After the lead arranger and the firm agree on these terms, the lead arranger invites other lenders to participate in the syndicated loan, which means that the interaction between the firm and participants is limited (Dennis and Mullineaux, 2000; Sufi, 2007; Ivashina, 2009). Hence, these participants do not face the loan demand directly, and their shares are not likely to be 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. To do a within loan comparison, we include loan fixed effects in our preferred specification and estimate the following model:

$$\text{Lender Share}_{\text{b,l,f,t}} = \alpha_{\text{l}} + \beta \text{CCPI}_{\text{c,t}} + \gamma \mathbf{X}_{\text{b,t-1}} + \varepsilon_{\text{b,l,f,t}} \tag{1}$$

where Lender $\text{Share}_{\text{b,l,f,t}}$ is the cross-border loan share that bank b finances in loan l to firm f in year t. The variable of interest is $\text{CCPI}_{\text{c,t}}$, which measures the climate policy stringency of the country where the bank is located (hereafter lender-country) and is indexed by c. $\mathbf{X}_{\text{b,l,t-1}}$ 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 (ROAE, Net interest margin, log of customer deposits) and bank's liquid assets position (liquidity ratio). α_l denotes the vector of loan fixed effects. We cluster the standard errors at the lender's country-year level as it is the unit of treatment (Abadie et al., 2017).

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. As these variables can be correlated with climate policy stringency, we collect related variables and include them in the regression models.

Even though we have a rich set of controls, there can still be omitted variables that may bias our results. We use an instrumental variable strategy to mitigate related concerns and have an exogenous variation in climate policy stringency. Namely, we use the change in Green Party share in the parliament as an instrument for the climate policy stringency and refer to them as the Green Party share. Political parties that mainly focus on environmental protection, the Green Party, were first established around the early 1970s.[23] In tandem with increasing concerns regarding climate change in public, these parties have started to have more prominent roles in politics. As the main agenda of these parties is about the protection of the environment and actions against climate change, a change in their shares in the parliament should reflect the perception of environmental problems. For instance, an increase in Green Party share should predict stringent climate policies. Note that the relevance of Green Party share does not require the Green Party to be the ruling party or be a part of the ruling coalition. The reason is that the parties in charge can adjust their actions accordingly after observing the changes in Green Party's share. Moreover, to make sure that the relevance condition is satisfied, we let 1 year to pass after the election and we restrict our sample with European lenders, considering the Green Party's relevance in Europe.

In addition to the relevance condition, Green Party share should satisfy the exclusion restriction. In our context, exclusion restriction means that the changes in Green Party share should not affect the cross-border lending other than its effect through the climate policy stringency. This assumption would be violated, for instance, if Green Party share affect both the climate policy stringency and economic conditions as changes in economic conditions are likely to affect cross-border lending. The fact that the changes in Green Party share occur only after elections suggests that this assumption is satisfied in our setting. Typically, elections are held on a predetermined cycle, which means that the economic conditions and the election cycles are not likely to affect each other. This suggests that

[23] There can be several parties that focus on environmental protection. We combine all of such parties and mention them as the Green Party for the ease of exposition.

the timing of changes in Green Party share is not related to economic conditions. Thanks to this timing, these changes provide us the exogenous variation needed to identify the effect of climate policy stringency on cross-border lending. In Section 4, we provide supporting evidence that changes in Green Party share are orthogonal to the economic conditions.

4 Results

In this section, we use syndicated loans for cross-border lending and the CCPI for climate policy stringency to study whether banks use cross-border lending to react to changes in 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 and an instrumental variable strategy and a rich set of control variables to mitigate concerns related to omitted variable bias. In Section 4.2, we provide our findings regarding the underlying mechanism. Section 4.3 concludes this section with additional analysis that exploits lender and regional heterogeneity.

Before moving to the regression models, Figure 3 plots a strong and positive correlation between the CCPI and cross-border loans 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 CCPI and loan supply. We use the regression models to document that this positive correlation is indeed driven by banks' reaction to the 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 CCPI 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 the CCPI.

For instance, observing an increase in CCPI 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 high CCPI 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 high CCPI 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 fixed effects in Column (2). The size of the estimated coefficient indicates that the loan share of the lender increases by 10 percent when its home country's CCPI increases by 24 units−the increase in CCPI that the United States experienced between 2007 and 2017. In Column(3), we include year fixed effects to control for time effects. 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 at the same year.

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). Given that participants do not have a direct relationship with the firm except the lead arranger in a syndicated loan, the assumption is highly likely to hold for lenders in the same syndicated loan. This implies that comparing lenders in the same loan would enable us to control for 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). The magnitude of the coefficient in this within-loan model is similar to the ones in the previous models, which mitigates the concerns about loan demand.

In addition to the loan demand, uncontrolled bank characteristics can bias the estimations. We already control for observable bank characteristics starting from Column (1).

However, there could be unobservable bank characteristics that are correlated with CCPI. To control for such bank unobservables, we use one syndicated loan market feature: bank groups can participate in the syndicated loan market with several subsidiaries. Being a part of the same group, it is likely that these subsidiaries share similar business models. Thus, comparing the loan supply of subsidiaries of the same bank group holds the effect of bank characteristics on loan supply constant. To do so, we include bank group fixed effects in Column (6). Furthermore, these subsidiaries may be located in different countries, which allows us to compare subsidiaries of the same group in the same year. We make this comparison in Column (7) by including bank group×year fixed effects. We have positive and significant coefficients in both columns.[24]

After establishing that the positive correlation between cross-border lending and CCPI is not driven by loan demand or bank characteristics, we now turn to the concern related to variables correlated with both CCPI and loan supply. Being a weighted average of 14 different climate policy-related measures, CCPI can be correlated with other country-level variables. For instance, an improvement in the economic conditions can enable residents of a country to be more careful about the environment, leading to a higher CCPI score. Moreover, cultural differences among the countries can be a factor in the observed heterogeneity in CCPI.[25] 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 CCPI 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.

[24]In Table A1 of the Appendix, we investigate the relationship between exposure to lenders' CCPI and carbon emissions at the borrower level. If the positive relationship is driven by loan demand, we may find a change in carbon emissions, reflecting firms' desire to alter their carbon print. Instead, if the positive effect is driven by loan supply, there may not be a change in carbon emissions. In line with a loan supply channel, we do not find any significant effect of exposure to lenders' CCPI on the carbon emissions of the borrowers.

[25]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).

We mitigate the concern about the omitted variables in two steps. First, we collect variables that are shown to be related to cross-border lending in the literature and include 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. 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 (2). We use population growth, share of old and young workforce in Column (3) for differences in demographics. Finally, we follow the literature and include indices for credit and property rights with the log of contract enforcing days to control for legal environment of the lender's home country (Qian and Strahan, 2007; Houston et al., 2012). In all of these specifications, the positive coefficient of CCPI survives, and its magnitude is similar to the ones we have in Table 2.

Despite the rich set of control variables, the error term of the model in Equation 1 can still be correlated with CCPI, which necessitates an exogenous variation in CCPI. In the second step, we aim to obtain the needed exogenous variation by using the changes in the Green Party share in the parliament as an instrument for CCPI. As discussed in Section 3, there is little doubt that this instrument is relevant for CCPI owing to the main agenda of the Green Party. The results in Column (1) of Table 4 show that indeed the Green Party share is relevant for CCPI. Consistent with intuition, CCPI increases when there is an increase in the Green Party share. To see whether the positive relationship between CCPI and IV is strong enough, we report the efficient F-statistics developed by Olea and Pflueger (2013).[26] Reassuringly, the effective F-statistics in our specifications are larger than the threshold level of 23.1 for 10 percent worst-case benchmark derived by Olea and Pflueger (2013), alleviating the concerns about weak instrument. We report the second-stage estimates with the efficient F-statistics from the first-stage in the remaining columns. In Column (2), we

[26] The efficient F-statistics is robust to heteroscedasticity, serial correlation, and clustering (Olea and Pflueger, 2013).

start with loan fixed effects and estimate a positive and statistically significant coefficient for the instrumented CCPI.[27] This positive coefficient lends strong support to our interpretation of the earlier results: banks increase their cross-border lending as a reaction to stringent home-country climate policy. In Columns (3) and (4), we consecutively include economic condition and bank group level controls. Doing so yields very similar estimates.

As argued in Section 3, the most likely way the exclusion restriction is to be violated is that the Green Party share is correlated with economic conditions. If this is the case, then CCPI instrumented by the Green Party share could still pick up the effect of economic conditions. On the other hand, the Green Party share may be uncorrelated to economic conditions due to election cycles being predetermined and unrelated with economic conditions. We investigate the correlation between the economic conditions and the Green Party share in Table 5, in which we use $\log(\text{GDP})_{pc}$, $\Delta log(GDP)$, Credit to GDP ratio, and Unemployment Rate as proxies for the economic conditions. First, in Panel A, we regress these four variables on the change in Green Party share one by one, considering the possibility that the Green Party share can influence the economic conditions.[28] Supporting the exclusion restriction, the estimated coefficient is insignificant in all of these models. In Panel B, we consider another possibility in which economic conditions influence the Green Party share. To assess this possibility, we regress the change in Green Party share on the lagged values of economic condition proxies separately in the first four columns and on all economic condition variables in the same model in Column (5). In line with the exclusion restriction, the economic condition variables have insignificant coefficients in all of these models. Overall, the results in Table 5 provide consistent evidence that the relationship between economic

[27] Lee et al. (2021) report that the adjustment factor is 1.147 when the 1^{st}-Stage F-statistics is 33.457. This adjustment factor indicates that the t-statistics of $\widehat{CCPI}_{\text{lender}}$'s coefficient should be larger than 2.30 to be significant at 5 percent level. On Column (2), the t-statistics of $\widehat{CCPI}_{\text{lender}}$ is 3.75, which means that the coefficient is significant at 5 percent.

[28] We do not use the whole election cycle in this panel as we do in Table 4. Instead, we use the observations one year after the election. Note that this is a conservative sample decision since using the whole election cycle reduces the statistical power of the change in Green Party share. The reason is that the instrumental variable does not change within the election cycle. When we use the whole election cycle, the explanatory power of the change in Green Party share is even smaller, in line with this argument.

conditions and the Green Party share does not pose a threat to the identification.

Despite the lack of correlation between economic conditions and the Green Party share, 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 Green Party share 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: $Lender\ share = \beta\, CCPI + \gamma\, \Delta Green\ Party\ share + \epsilon$. 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 $\Delta Green\ Party\ share$ (γ) should be to make the effect of $CCPI$ (β) insignificant. We report the results of this method in Figure 4 at 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 4 illustrates that the direct effect of the Green Party should be as large as its effect through climate policy stringency to make β insignificant at 10 percent. Considering the lack of correlation between economic conditions and the Green Party share, we deem this implausible. An additional evidence comes from a comparison of Columns (2)-(4) in Table 4. When we include economic conditions and bank-level control variables in the model, we see that the coefficient of instrumented CCPI stays remarkably stable, despite a relative increase in R^2. In the spirit of measurement of omitted variable bias framework (Altonji et al., 2005; Oster, 2017), this stability implies that the magnitude of the omitted variable bias is limited.

4.2 Underlying 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 as a regulatory arbitrage tool. Regulatory arbitrage 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 stricter regulation at home (Acharya, 2003). Even though regulatory arbitrage might allow banks to increase their charter value if the regulations are costly, it will do so at the expense of the effectiveness of the regulations (Houston et al., 2012; Karolyi and Taboada, 2015). For climate policies, a decline in effectiveness might generate far-reaching negative externalities due to the nature of climate change.

The first evidence for the underlying mechanism comes from the heterogeneity among the borrower countries' climate policy stringency. Regulatory arbitrage in the context of climate policies has two implications regarding this heterogeneity among the borrowers. First, if the underlying mechanism is regulatory arbitrage, 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 lender. We test this hypothesis on the first two columns of Table 6, where we interact $\text{CCPI}_{\text{lender}}$ with $\text{CCPI}_{\text{borrower}}$. In line with regulatory arbitrage, 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. Second, the regulatory arbitrage mechanism predicts that 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 the lender's exposure to stringent climate policies. The remaining columns in Table 6 analyze this 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 $\text{CCPI}_{\text{lender}} > \text{CCPI}_{\text{borrower}}$. In contrast, it has an economically and statistically insignificant coefficient when $\text{CCPI}_{\text{lender}} < \text{CCPI}_{\text{borrower}}$, which provides additional support to the regulatory arbitrage mechanism.

The second evidence comes from the heterogeneity in lender countries' bank supervision environment. In essence, regulatory arbitrage works against the efforts of the lender countries' regulators. This suggests that, in a country with strong bank supervision, lenders may be less willing to create the shortcut through cross-border lending since such activity can attract the attention of the supervisors with a possible penalty. On the contrary, a weak supervision environment can facilitate regulatory arbitrage as a new regulation against this action is less likely. One implication of this argument is that the effect of the climate policy stringency on cross-border lending should be larger in countries with weak bank supervision. We test this hypothesis in Table 7, where we use two different bank supervision environment variables. In Panel A of Table 7, 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 Panel B, we use *bank supervisory power*, which shows 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 intro 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 also point out that the increase in cross-border lending is driven by the regulatory arbitrage channel.

Another way to investigate the underlying mechanism is combining cross-border lending with domestic lending and using granular firm-level carbon risk data. The regulatory arbitrage 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, it predicts an increase in cross-border lending to borrowers with high carbon risk. We extend our data set and include domestic syndicated loans to assess these two predictions together. Then, 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.[29] These

[29]Due to data availability of firm-level carbon risk, the number of observations declines in this sample.

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 1 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 regulatory arbitrage, High Carbon Intensity Risk$\times\text{CCPI}_{\text{lender}}$ has a positive 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 Same Country$\times$High Carbon Intensity Risk$\times\text{CCPI}_{\text{lender}}$. This negative coefficient shows that credit supply to domestic firms decreases when $\text{CCPI}_{\text{lender}}$ increases if the domestic firm has a high carbon risk.

One remaining question regarding the regulatory arbitrage mechanism is why a more stringent climate policy makes domestic lending less appealing. Higher stringency aims to reduce the carbon print of the economy, which entails a reduction in carbon emissions. A reduction in emissions may require a change in the business model or in the production process. Also, existing inventories and machinery may lose value due to the required changes (Litterman, 2021). These suggest that a stringent climate policy may decrease the firm profitability, making domestic lending less appealing. To see whether this is the case, we regress firm profit variables on CCPI in Table 9. Specifically, we use Return on Equity, Return on Capital, Net Profit Margin, and Operating Margin as firm profit indicators at the country level.[30] Table 9 documents that climate policy stringency is negatively correlated with all four profit variables. This finding implies that the changes that a stringent climate policy induces on firms may hurt the firms' profitability, which in turn can lead the lenders to increase their lending abroad.

In the last table of this section, to provide further insight into the underlying mechanism, we investigate which component of the CCPI is more important for the increase in cross-

[30]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 country-year level. These aggregate values are therefore less susceptible to outliers.

border lending. As explained in Section 2, CCPI consists of four main categories: GHG Emission, Renewable Energy, Energy Use, and Climate Policy. For each category, an increase in value represents a more environment-friendly policy (Burck et al., 2016). Among these four categories, as their names suggest, Climate Policy captures policy actions against climate change and is forward-looking. While, other three categories capture realized outcomes of such policies and actions. Therefore, we expect to find that Climate Policy is more important than the other categories if regulatory arbitrage is the underlying mechanism. To see this, we take four categories and run horse-race regression models in Table 10. With different sets of control variables and fixed effects, Table 10 shows that only Climate Policy has consistently positive and significant coefficients. This finding indicates that banks react to policies about climate change instead of realized outcomes of such policies. Moreover, this finding supports the interpretation that banks use cross-border lending as a regulatory arbitrage tool.

4.3 Additional analysis

This section continues our analysis by exploring the heterogeneity in lender characteristics and the regional patterns. We start with lender characteristics in Table 11. In Columns (1) and (2) of Table 11, 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 as for such banks, cross-border lending is easier to conduct, and the fixed costs attached to cross-border lending can be less important. 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. In the last two columns, we investigate the influence of banks' NPL ratio on the effect of climate policy stringency. Regulatory arbitrage has a special prediction for the NPL ratio, which is that the effect can be stronger for the 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 is stronger. In line with this argument, we find that the effect is significantly larger for banks with a high NPL ratio.

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 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 12. On this table, we categorize borrowers into five locations: the USA, 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 conclude this section by exploring alternative specifications to test the effect of climate policy stringency on cross-border lending. In the first alternative specification, we use loan amounts instead of loan shares. One concern with using loan shares as a measure of cross-border lending can be that if the loan size gets smaller as climate policy becomes more stringent, the amount of lending of a lender to a borrower can be smaller, even though the loan share is higher. To mitigate this concern, we use log(loan amount) as the dependent variable in Table A2 of the Appendix. Similar to our main table, we saturate the model with the loan fixed effects and bank group×year fixed effects. We estimate a positive and significant coefficient in every model, which confirms the positive impact of climate policy stringency on cross-border lending.

In the second alternative specification, we aggregate our loan level data up to lender level (De Haas and Van Horen, 2013). Even though it is less granular, the lender-borrower country-year level data considers the overall lending of a lender to each country, providing a broader picture of cross-border lending. This aggregated data enables us to consider two different dependent variables: the number of syndicated loans a lender extends to a country, and the total amount of loans a lender extends to a country. We use log(Number of loans) as the dependent variable in the first four columns of Table A3 in the Appendix and log(Loan amount) in the remaining four columns. Furthermore, instead of using $\text{CCPI}_{\text{lender}}$ as the main independent variable we use Δ CCPI, which is the difference between $\text{CCPI}_{\text{lender}}$ and $\text{CCPI}_{\text{borrower}}$. 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 lenders with different ΔCCPI to the same borrower country. In all specifications, we estimate positive and significant coefficients for the number of loans and loan amount. These findings indicate that the positive effect of climate policy stringency is robust to alternative specifications and data structures.

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 for the ones who do not want to comply with stricter climate policies. In this paper, we focus on lenders and try to understand whether they exploit the heterogeneity in climate policies with 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 lenders.

We find that lenders react to a more stringent climate policy at home by increasing their cross-border lending. Specifically, lenders increase their shares in cross-border syndicated loans by 8.6 percent when the climate policy stringency of their home country increases by one standard deviation. To establish that the effect is not driven by loan demand, we use the granularity of syndicated loans and compare the lenders within the same loan by employing loan fixed effects. To mitigate concerns about omitted variables, we instrument climate policy stringency with Green Party shares in the parliament. Thanks to the predetermined election cycles, we show that these shares are not correlated with economic conditions, which suggests that these shares provide us arguably exogenous variation in climate policies.

Why do we observe the increase in cross-border lending? Our findings are in line with a regulatory arbitrage behavior, in which the increase in cross-border lending reduces lenders' 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 firm profits as a possible explanation for why lenders have incentives to increase their cross-border lending.

Our paper documents one adverse effect of the 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 externalities. 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 be helpful for policymakers to improve international coordination and develop more effective policies.

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Figures and Tables

Figure 1: **Global development of climate policy stringency**

These maps show the climate policy stringency index (Climate Change Performance Index) for the 39 countries included at the beginning (2007 in Panel A) and end (2017 in Panel B) of our sample period. The CCPI score takes values in the interval [0;100], where higher values proxy a country with more stringent climate policy. The shade in color proxies the value for each country. Darker areas indicate higher values of the CCPI, or more stringent climate policy. Countries with no color shade are not part of our sample. For the list of the countries included in our sample, see Figure A1.

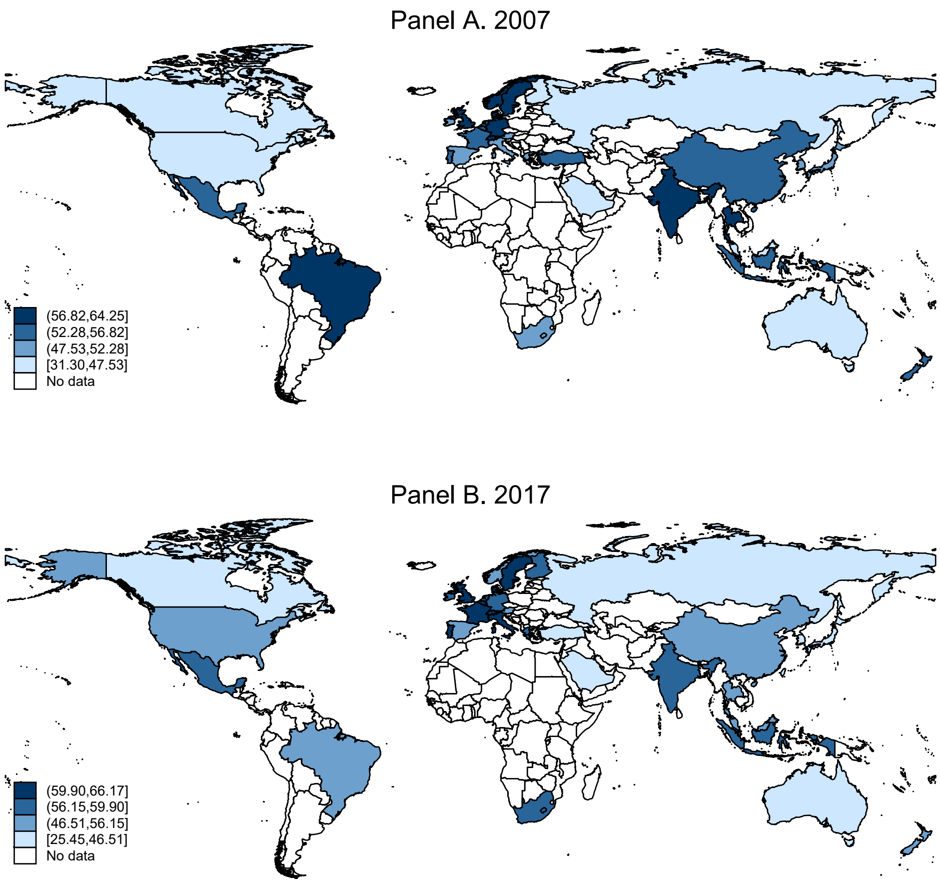

Figure 2: **Variation in the climate policy stringency**

This figure reports the average value against the standard deviation of the climate policy index (Climate Change Performance Index) 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 climate policy index. For the list of the countries included in our sample, see Figure A1.

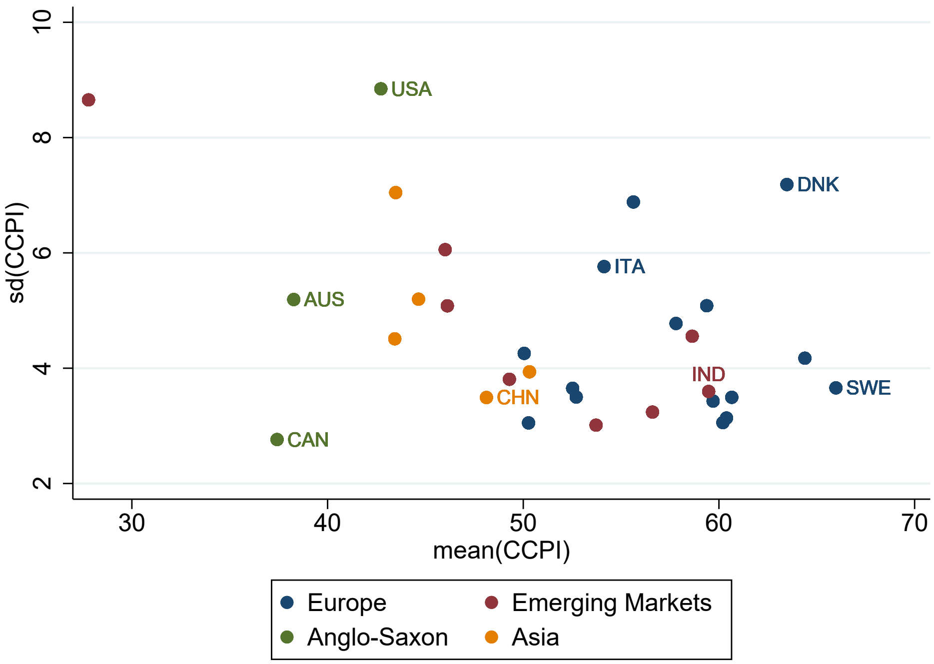

Figure 3: **Correlation between home country climate policy and cross-border bank lending**

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 A4.

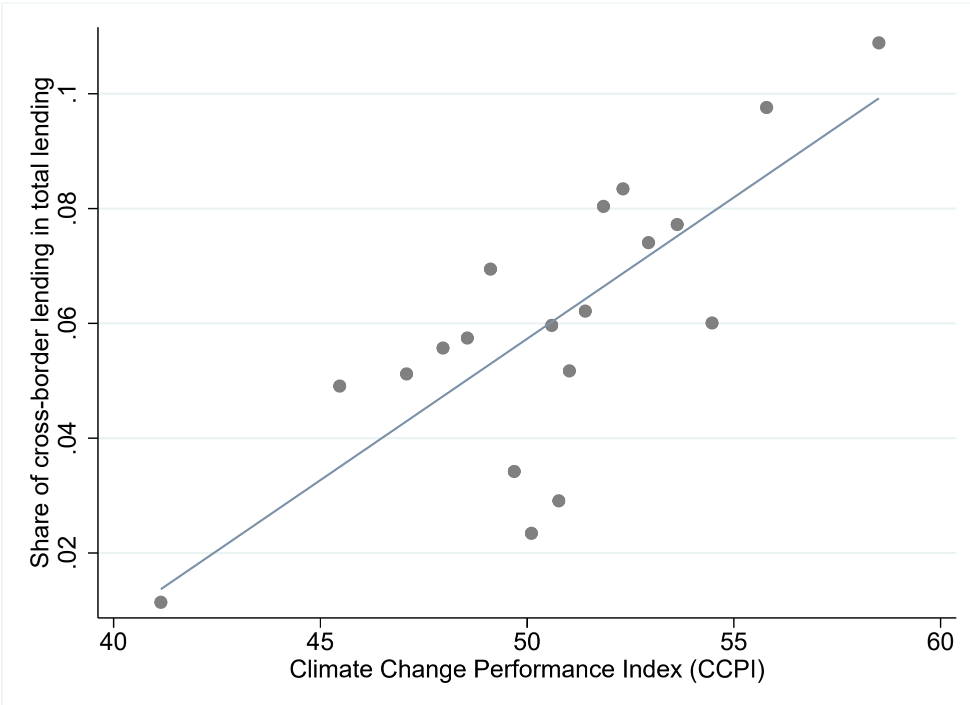

Figure 4: **Green Party share and the exclusion restriction**

This figure shows the estimated coefficient of $\text{CCPI}_{\text{lender}}$ 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 $\text{CCPI}_{\text{lender}}$ with the method developed by Conley et al. (2012). The x-axis shows the direct effect Green Party vote shares on cross-border lending after controlling for its effect through $\text{CCPI}_{\text{lender}}$ and country level variables. For variable definitions, see Table A4.

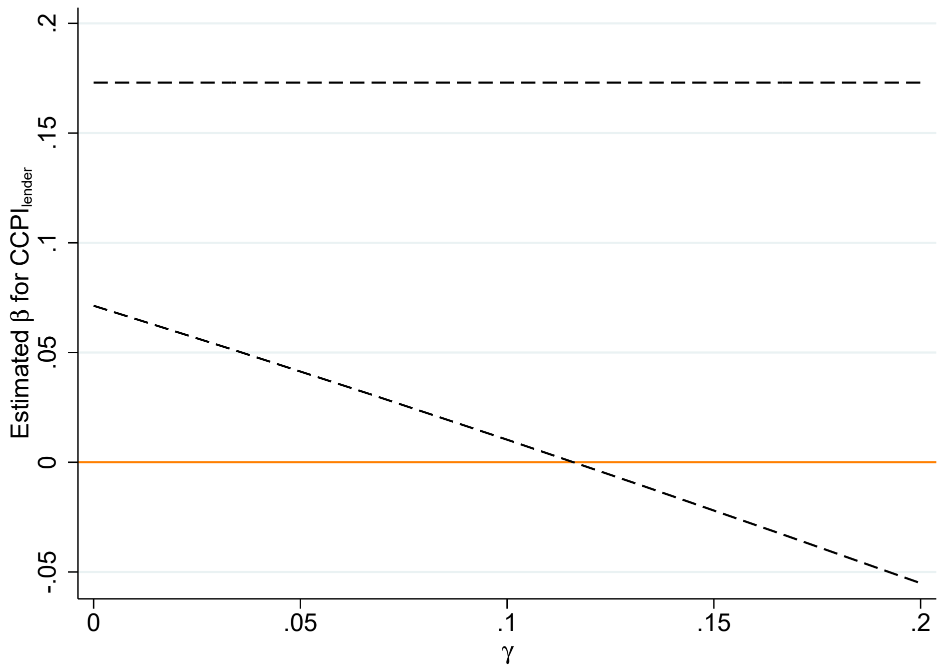

Table 1: **Summary statistics**

This table provides summary statistics of the main variables for the period 2007-2017. The sample consists of cross-border loan's shares in the syndicated loan market. Balance sheet variables are at an annual frequency. The mean, standard deviation, minimum and maximum values are shown. For variable definitions, see Table A4.

	Obs.	Mean	Std. Dev.	Min.	Max.
Lender share	12,478	7.722	7.989	0.070	94.210
$CCPI_{lender}$	12,478	55.689	8.179	22.848	76.620
$CCPI_{borrower}$	12,478	49.961	8.887	22.848	76.620
Bank-level controls					
log(Total assets)	12,478	28.097	3.088	11.169	36.838
Tier 1 capital ratio	12,478	12.342	7.255	3.700	182.760
log(Customer deposits)	12,478	27.260	3.375	6.639	36.813
Liquidity ratio	12,478	49.097	35.340	0.720	395.494
ROAE	12,478	5.626	11.212	-223.690	46.090
Net interest margin	12,478	1.481	0.782	-0.130	9.170
Country-level controls					
log(GDP per capita)	11,942	10.497	0.709	6.906	11.685
GDP growth	11,942	1.949	2.605	-8.075	14.526
Domestic credit to GDP	11,705	121.545	37.846	25.456	206.671
Unemployment rate	11,942	7.562	3.457	0.489	27.071
Common language	11,510	0.246	0.431	0	1
log(Distance)	11,510	7.908	1.025	4.798	9.384
Top 5 bank concentration	12,259	73.559	14.744	28.970	100
Population growth	11,943	0.547	0.532	-1.854	5.322
Young workforce	11,942	26.572	4.370	15.767	55.337
Old workforce	11,942	25.379	6.296	4.192	45.125
Capital regulatory index	9,004	6.851	1.778	2	10
Independence of supervisory authority	10,688	2.020	0.813	0	3
Bank supervisory power	11,264	10.106	1.909	6	16
Property rights	11,838	77.153	18.426	20	97.1
Legal rights index	5,514	5.820	2.782	1	12
log(Contract enforcing days)	6,618	4.598	0.494	3.258	5.720
Financial liberalization index	11,838	67.711	14.805	20	90
Others					
Climate $policy_{lender}$	12,478	12.053	4.231	0	20
Renewable $energy_{lender}$	12,478	2.617	1.704	0.023	8.094
Energy use_{lender}	12,478	5.715	1.439	1.017	9.124
$CO_{2lender}$	12,478	35.304	5.257	9.570	45.564
Δ Green Party Shr.	7,573	0.286	1.410	-4.500	6.667
High Carbon Intensity Risk	1,419	0.725	0.447	0	1
log(Loan amount)	12,478	17.352	1.539	6.354	21.563
Same Country	28,217	0.512	0.499	0	1
log(Loan volume)	4,211	19.488	2.180	13.153	25.155
log(Number of loans)	4,211	2.192	1.178	0.693	6.704

Table 2: **The 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), 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CCPI_{lender}$	0.027	0.043***	0.044***	0.045***	0.042***	0.042***	0.081***
	(0.019)	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)	(0.016)
Controls & Fixed Effects:							
Bank Group Controls	✓	✓	✓	✓	✓	✓	
Borrower FE		✓	✓				
Year FE			✓				
Borrower × Year FE				✓			
Loan FE					✓	✓	✓
Bank Group FE						✓	
Bank Group × Year FE							✓
Obs.	12,478	12,478	12,478	12,478	12,478	12,394	12,105
R^2	0.004	0.735	0.736	0.809	0.842	0.863	0.878
Mean(Lender Share)	7.722						

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 $CCPI_{lender}$. The sample covers the period 2007-2017. Economic controls are log(GDP per capita), domestic credit to GDP, unemployment rate, GDP growth. Culture controls are log(Distance) and common language. Domestic bank competition control is Top 5 bank concentration. Demographics controls are log(total population), young workforce, old workforce, and population growth. Bank regulation controls are independence of supervisory authority and capital regulatory index (Barth et al., 2013). Institution controls are legal rights index, financial freedom, property rights, and log(Contract enforcing days). 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share					
	(1)	(2)	(3)	(4)	(5)	(6)
$CCPI_{lender}$	0.039***	0.034***	0.032***	0.037***	0.045**	0.058*
	(0.008)	(0.008)	(0.008)	(0.009)	(0.019)	(0.033)
Controls & Fixed Effects:						
Loan FE	✓	✓	✓	✓	✓	✓
Bank Group Controls	✓	✓	✓	✓	✓	✓
Economic Controls	✓	✓	✓	✓	✓	✓
Culture Controls		✓	✓	✓	✓	✓
Bank Competition Controls			✓	✓	✓	✓
Demography Controls				✓	✓	✓
Bank Regulation Controls					✓	✓
Institutions Controls						✓
Obs.	11,530	11,076	11,076	11,076	5,810	3,571
R^2	0.853	0.854	0.854	0.854	0.865	0.872
Mean(Lender Share)	7.722					

Table 4: **Green Party share as an instrument for climate policy stringency**

This table reports estimates from Equation 1 in which CCPI is instrumented by Δ Green 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 country controls. Column (4) includes bank 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, unemployment rate, a dummy variable that is equal to one if the two countries share the same language, and distance between the two countries. Bank controls are 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

	$\text{CCPI}_{\text{lender}}$	Lender Share		
	(1)	(2)	(3)	(4)
Δ Green Party Share	1.620***			
	(0.277)			
$\widehat{CCPI}_{\text{lender}}$		0.120***	0.122***	0.121**
		(0.032)	(0.031)	(0.051)
Controls & Fixed Effects:				
Country Controls			✓	✓
Bank Group Controls				✓
Loan FE	✓	✓	✓	✓
Obs.	3,216	3,216	3,084	3,084
R^2	0.340	0.026	0.033	0.063
1^{st} Stage Eff. F-stat	34.252	34.252	35.612	24.050
Mean(Lender Share)	7.716			

Table 5: **Green Party share and economic conditions**

This table shows the correlation between the Green Party vote shares and macroeconomic variables. Panel A reports results of regression models in which GDP per capita, Log change in GDP, domestic credit to GDP ratio, and unemployment rate are regressed on Δ Green Party Share$_{t-1}$. Panel B reports results of regression models in which Δ Green Party Share is regressed on GDP per capita, log change in GDP, domestic credit to GDP ratio, and unemployment Rate. The sample covers the period 2007-2017. 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

Panel A

	(1)	(2)	(3)	(4)
	$\log(GDP)_{pc}$	Δ log(GDP)	Credit to GDP	Unemp. Rate
	(1)	(2)	(3)	(4)
Δ Green Party Share$_{t-1}$	0.014	0.168	-1.507	0.147
	(0.024)	(0.294)	(2.876)	(0.378)
Obs.	1,602	1,602	1,600	1,602
R^2	0.021	0.019	0.008	0.011

Panel B

	(1)	(2)	(3)	(4)	(5)
	Δ Green Party Share				
	(1)	(2)	(3)	(4)	(5)
$\log(GDP)_{pc,\ t-1}$	0.696				0.902
	(1.026)				(0.731)
Δ $\log(GDP)_{t-1}$		-0.225			-0.255
		(0.145)			(0.158)
Credit to GDP_{t-1}			0.002		0.006
			(0.005)		(0.006)
Unemp. $Rate_{t-1}$				-0.021	0.011
				(0.177)	(0.184)
Obs.	1,622	1,622	1,622	1,625	1,621
R^2	0.008	0.093	0.002	0.001	0.123

Table 6: **Underlying mechanism: Cross-border lending as a regulatory arbitrage tool**

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) shows 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Interaction		$CCPI_{borrower} < CCPI_{lender}$			
	(1)	(2)	(3) Yes	(4) No	(5) Yes	(6) No
$CCPI_{lender}$	0.046***	0.043***	0.061***	0.008	0.060***	0.009
	(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)				
Controls & Fixed Effects:						
Bank Group Controls	✓	✓	✓	✓	✓	✓
Borrower × Year FE	✓		✓	✓		
Loan FE		✓			✓	✓
Obs.	12,478	12,478	7,980	3,860	7,763	3,519
R^2	0.809	0.842	0.812	0.819	0.851	0.841
Mean(Lender Share)	7.722					
Difference			0.052**		0.052**	

Table 7: **How does domestic bank regulation influence climate policy-induced 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. Panel A splits the sample into three in terms of the *Independence of the Bank Supervisory Authority.* Panel B splits the sample into three in terms of the *Bank Supervisory Power.* 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

Panel A

Lender Share	Ind. of Bank Supervisory Auth.		
	(1)	(2)	(3)
	Low	Medium	High
$CCPI_{lender}$	0.071***	0.028	-0.001
	(0.024)	(0.018)	(0.022)
Controls & Fixed Effects:			
Bank Group Controls	✓	✓	✓
Loan FE	✓	✓	✓
Obs.	2,353	2,693	2,826
R^2	0.827	0.867	0.867
Mean(Lender Share)	7.722		

Panel B

Lender Share	Bank Supervisory Power		
	(1)	(2)	(3)
	Low	Medium	High
$CCPI_{lender}$	0.071***	0.043	0.027**
	(0.021)	(0.069)	(0.011)
Controls & Fixed Effects:			
Bank Group Controls	✓	✓	✓
Loan FE	✓	✓	✓
Obs.	2,963	2,181	3,420
R^2	0.874	0.841	0.849
Mean(Lender Share)	7.722		

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 A4. *** 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)
Controls & Fixed Effects:					
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				

Table 9: **Climate policy stringency and corporate profits**

This table documents the negative correlation between climate policy stringency and corporate profits. The sample covers the period 2013-2017. Column (1) uses Return on Equity as dependent variable. Column (2) uses Return on Capital as dependent variable. Column (3) uses Net Profit Margin as dependent variable. Column (4) uses Operating margin as dependent variable. Control variables and fixed effects are indicated at the bottom of each column. Control variables are country-level population growth, ratio of young work force, 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 A4. *** 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 & Fixed Effects:				
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 10: **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 A4. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share				
	(1)	(2)	(3)	(4)	(5)
Climate policy$_{\text{lender}}$	0.040	0.063***	0.058***	0.069***	0.065***
	(0.038)	(0.013)	(0.013)	(0.012)	(0.013)
Renewable energy$_{\text{lender}}$	-0.234**	-0.031	0.056	0.020	0.037
	(0.095)	(0.037)	(0.053)	(0.053)	(0.055)
Energy use$_{\text{lender}}$	0.103	0.029	0.162*	0.039	0.027
	(0.148)	(0.057)	(0.082)	(0.079)	(0.084)
$CO_{2\text{lender}}$	0.053	0.046**	0.012	0.035	0.032
	(0.040)	(0.018)	(0.024)	(0.022)	(0.023)
Controls & Fixed Effects:					
Bank Group Controls	✓	✓	✓	✓	✓
Borrower FE		✓	✓		
Year FE			✓		
Borrower × Year FE				✓	
Loan FE					✓
Obs.	12,478	12,478	12,478	12,478	12,478
R^2	0.006	0.735	0.736	0.809	0.842
Mean(Lender Share)	7.722				

Table 11: **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 (total assets). Columns (3) and (4) split the sample into two with respect to the ratio of cross-border lending to total lending. Columns (5) and (6) split the sample into two with respect to the Tier 1 capital ratio. Columns (7) and (8) split the sample into two with respect to the non-performing loans ratio (NPL). 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Size		Cross-Border		Capital		NPL	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Low	High	Low	High	Low	High
$CCPI_{lender}$	0.018**	0.061***	0.022**	0.107***	0.053***	0.045***	0.031*	0.097***
	(0.008)	(0.010)	(0.009)	(0.013)	(0.013)	(0.009)	(0.018)	(0.031)
Fixed Effects:								
Loan FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	5,356	5,337	5,328	5,459	5,406	5,626	847	881
R^2	0.843	0.858	0.842	0.846	0.841	0.861	0.838	0.808
Mean(Lender Share)	7.722							
Difference	0.043***		0.085***		-0.008		0.065*	

Table 12: **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 belonging to the same geographical area. The dependent variable is Lender share and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. European countries are Austria, Belgium, Denmark, France, Germany, Greece, Netherlands, Ireland, Italy, Norway, Spain, Portugal, and United Kingdom. Emerging market countries are Saudi Arabia, China, Chinese Taipei, India, Brazil, Russian Federation, Indonesia, South Africa, Malaysia, and Turkey. Asian countries are Japan, Singapore, Korea, Chinese Taipei, and China. Anglo-Saxon countries are 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Europe vs USA	Europe vs Emerging markets	Europe vs Europe	Europe vs Asia	Europe vs Anglo-Saxon
	(1)	(2)	(3)	(4)	(5)
$CCPI_{lender}$	0.029	0.131***	0.008	0.110	0.040*
	(0.026)	(0.032)	(0.016)	(0.071)	(0.023)
Controls & Fixed Effects:					
Bank Group Controls	✓	✓	✓	✓	✓
Loan FE	✓	✓	✓	✓	✓
Obs.	3,751	885	3,069	371	4,091
R^2	0.820	0.894	0.907	0.864	0.833
Mean(Lender Share)	7.722				

Appendix

Figure A1: **Average home country climate policy**

This graph reports the average Climate Change Performance Index (CCPI) for each country included in our sample over sample period 2007-2017. Average values of CCPI scores are: Australia (39.35), Austria (50.45), Belgium (60.44), Brazil (60.99), Canada (38.04), China (47.64), Chinese Taipei (44.48), Denmark (65.27), Finland (51.38), France (60.71), Germany (59.86), Greece (49.14), India (60.38), Indonesia (57.31), Ireland (51.18), Italy (54.26), Japan (43.62), Korea (46.28), Luxembourg (41.74), Malaysia (46.38), Mexico (60.81), Netherlands (52.65), New Zealand (51.39), Norway (57.16), Poland (54.80), Portugal (61.69), Russian Federation (48.74), Saudi Arabia (28.03), Singapore (49.16), South Africa (50.61), Spain (53.31), Sweden (65.69), Switzerland (62.68), Thailand (55.95), Turkey (47.07), United Kingdom (63.31), United States (47.74).

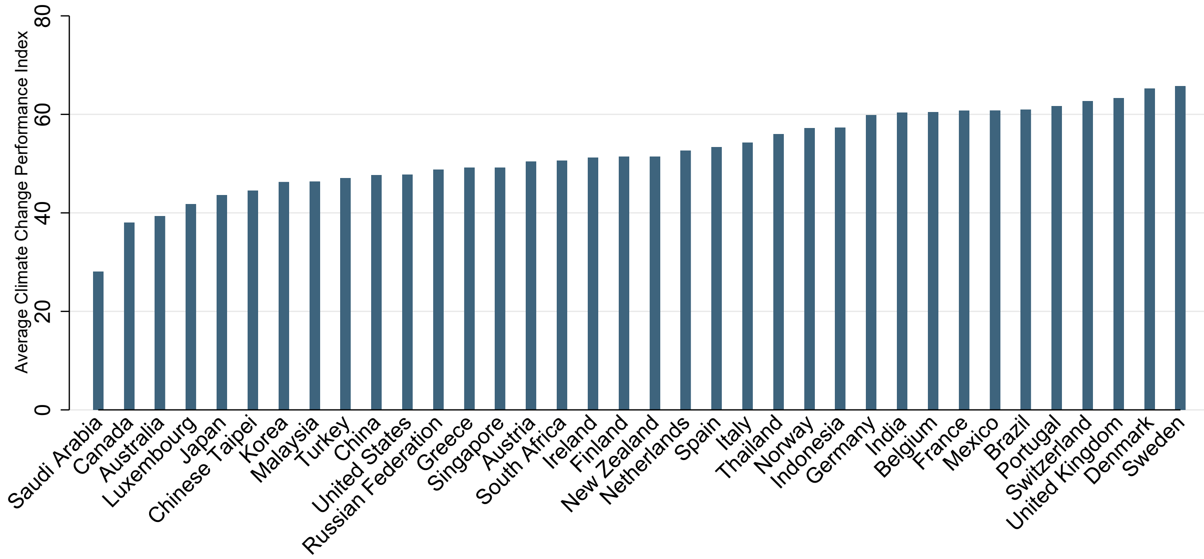

Table A1: **Climate policy stringency exposure from lenders and carbon emissions**

This table investigates the relationship between exposure to climate policy stringency via the lenders and the borrowers' carbon emissions. Dependent variable is the log of carbon emissions divided by total revenue. 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 A4. *** 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)
Fixed Effects:			
Borrower FE	✓	✓	✓
Obs.	253	201	153
R^2	0.980	0.992	0.991
Mean(Dep. Var.)	4.738		

Table A2: **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 A4. *** p<0.01, ** p<0.05, * p<0.1.

	log(Loan amount)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CCPI_{lender}$	0.029***	0.012***	0.012***	0.012***	0.012***	0.008***	0.016***
	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Controls & Fixed Effects:							
Bank Group Controls	✓	✓	✓	✓	✓	✓	
Borrower FE		✓	✓				
Year FE			✓				
Borrower × Year FE				✓			
Loan FE					✓	✓	✓
Bank Group FE						✓	
Bank Group × Year FE							✓
Obs.	12,478	12,478	12,478	12,478	12,478	12,394	12,105
R^2	0.069	0.728	0.732	0.804	0.902	0.925	0.930
Mean(log(Loan amount))	17.352						

Table A3: **Climate policy stringency differentials and cross-border credit flows**

This table shows estimation results from the bank-country pairs 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 destination country j –the country where borrower companies are located. The dependent variables are log(1+loan amount) or log(1+number of loans) and the main independent variable is ΔCCPI, which is equal to the difference between $\text{CCPI}_{\text{lender}}$ and $\text{CCPI}_{\text{borrower}}$. 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 A4. *** p<0.01, ** p<0.05, * p<0.1.

	log(Number of loans)				log(Loan amount)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ 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)
Controls & Fixed Effects:								
Borrower country FE		✓				✓		
Borrower country × Year FE			✓	✓			✓	✓
Bank Group Controls				✓				✓
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	0.373
Mean(dep. var.)	2.198				19.495			

Table A4: **Variable 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 Use	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 A4(cont.): **Variable description**

Variable name	Variable definition	Source
Distance (log)	Log of geographic distance borrower-lender's country.	Rose (2004)
Financial freedom index	An overall score (ranging between 0 and 100) capturing banking efficiency as well as a measure of independence from government control and interference in the financial sector at the country-year level. The higher the score, the lower the government interference.	The Heritage Foundation
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.	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.	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 the ownership rights; suspend the board decision to distribute dividends, among others.	Barth et al. (2013)
Green Party share (%)	Share of seats that the Green Party obtained during a given election at the country-level. The variable is calculated as the number of party seats won over total seats.	National Archives Election Results
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

Table A4(cont.): **Variable description**

Variable name	Variable definition	Source
High Carbon Intensity Risk	Dummy variable equal 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
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