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Abstract

We provide evidence that banks increase cross-border lending in response to higher climate policy stringency in their home countries. Saturating with granular set of fixed effects and including a rich set of control variables, we show that the increase in cross-border lending is not driven by loan demand and/or other bank home country characteristics. In line with banks use cross-border lending as a regulatory arbitrage tool, the increase in cross-border lending occurs only if banks' home countries have more stringent climate policy compared to their borrowers' countries. The effect is stronger for large, lowly capitalized banks with high NPL ratios and for banks with more experience in cross-border lending. Our results suggest that without a global cooperation, cross-border lending can be a channel that reduces the effectiveness of climate policies.

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. Despite this need, there is still a large heterogeneity across governments in terms of climate policy stringency.[1] 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 any efforts to combat climate change.[2] In a similar fashion, higher stringency can also affect bank behavior due to its possible negative 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.

We find that banks react to higher climate policy stringency in their home country by increasing their cross-border lending. More specifically, banks increase their shares in cross-border syndicated loans by 10 percent if policy of their home country increases by the increase that U.S.A. has experienced between 2007 and 2017. Using granular fixed effects, we show that the increase in cross-border lending is not driven by loan demand. Moreover, the increase in cross-border lending is robust to controlling for other home country characteristics, such as economic conditions, culture, legal environment, and demographics. Supporting our interpretation that this increase in cross-border lending reflects banks' aim to avoid the effects of a more stringent climate policy, we show that increase in cross-border lending occurs only if home country climate policy is more stringent than the borrower's country. 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 such policies.

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

[1] For instance, Germany has introduced financial aid to support research on technologies for decarbonising heavy industry, whereas the US Senate removed all measures targeted to decarbonise the industry sector from Infrastructure Investment and Jobs Act passed by the US Senate in August 2021 (the Climate Action Tracker)

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

(CCPI).[3] Being a popular index among both academicians and practitioners, the CCPI comes with two main advantages (Atanasova and Schwartz, 2019; Delis et al., 2019). First, being a weighted average of 14 different climate policy indicators, the CCPI is a broad and inclusive assessment of the countries' climate policy stringency. Second, it facilitates climate policy comparison of countries with different backgrounds as it summarizes the differences with one metric. We combine the CCPI with syndicated loan data, which we use to assess bank cross-border 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 too, as the lead arranger of a syndicated loan can take actions to reduce the information asymmetries. Therefore, a combination of the CCPI series and syndicated loan data provides us with a relevant setting to investigate whether banks alter their cross-border lending to react to a change in climate policy stringency.

A naive regression model, in which cross-border lending is regressed on the CCPI, can suffer from two main sources of endogeneity. The first one is about loan demand. Observing an increase in the CCPI of a country, a firm may increase its loan demand to the banks from that country. One reason can be that the firm can use a relationship with a bank from a high CCPI country as a signaling device. Or, the firm may want to increase its knowledge in efforts against climate change and a lending relationship with this bank can provide this knowledge. These arguments imply that without properly controlling for loan demand, the relationship between the CCPI and cross-border lending cannot be interpreted in terms of the loan supply. Using the granularity of the syndicated loan data, we control for loan demand by borrower $\times$ year fixed effects. Another concern can be that loan specific features, such as covenants or interest rate spreads, can be correlated with the CCPI, which implies that not controlling for these features can introduce a bias as well. We further saturate our regression models with loan fixed effects, which means that we keep both loan demand and loan features constant, which allows us to identify the credit supply effects of climate policy

[3] The CCPI is developed by Germanwatch e.V. 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 the CCPI in section 2.

stringency.

A second concern about the naive model is that there can be another country level characteristic that is correlated both with the CCPI and cross-border lending, and our results can be driven by this characteristic instead of by the CCPI. For instance, an improvement in economic conditions can lead to an increase in both the CCPI and cross-border lending. Or, a change in demographics of the country can affect the CCPI by altering the perception of the climate change and cross-border lending by affecting loan demand. To mitigate such concerns, we collect information about country level economic conditions, culture, legal environment, and demographics and include these variables into our models. Our results do not change when we control for these variables.

After documenting the robustness of a positive effect of a higher climate policy stringency on cross-border lending, we investigate how heterogeneity across lenders interacts with this positive effect. First, we document that the positive effect of climate policy stringency on cross-border lending occurs only if the home country of the lender has a more stringent climate policy compared with the borrower's country. This finding indicates that the banks use the cross-border lending as a device to mitigate the effects of the climate policy since it shows that banks increase their cross-border lending selectively. Second, we find that banks 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 banks that have higher cross-border loans in their books and for banks that face a higher nonperforming loans ratio (NPL). A higher cross-border loans ratio implies that the bank has more experience with cross-border lending, which means that it is easier for this bank 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 bank to engage with cross-border lending since more stringent climate policy can reduce the returns of the loans when the bank needs higher return rate due to high NPL ratio.

We continue our analysis by examining which categories of the CCPI is more important for the cross-border lending. The CCPI has four categories: Greenhouse Gas Emissions, Renewable Energy, Energy Use, and Climate Policy. Estimating horse-race regression models that includes these four categories, we find that Climate Policy is the most important category for the cross-border lending. This implies that banks indeed react to the actual measures taken by the respective domestic governments, instead of the realized outcomes of these measures in terms of emissions for example. This finding also lends support to our interpretation that the underlying mechanism of our findings is capturing regulatory arbitrage.

Our paper contributes to at least two strands of the literature. First, our paper speaks to the growing literature about the risks that climate change creates for the firms and how these risks affect the financing decisions (Matos, 2020). One of these risks is related with the regulations that are implemented to fight against climate change (Krueger et al., 2020; Seltzer et al., 2020). Due to firms' exposure to climate risks, investors and banks might ask for higher returns (Atanasova and Schwartz, 2019; Delis et al., 2019; Bolton and Kacperczyk, 2021). This can incentivize the firms to reallocate their facilities to the areas with less stringent climate policies (Bartram et al., 2021). We contribute to this literature by providing evidence that banks take actions to reduce the influence of climate policy stringency on their loan portfolios. More specifically, we show that banks react to stringent policies by increasing their cross-border lending to countries with less stringent climate policies.

We also add to the strand of literature that examines cross-border lending incentives. Cross-border lending can be an important tool to transmit shocks among the countries (Cetorelli and Goldberg, 2011; Giannetti and Laeven, 2012; Ongena et al., 2015; Claessens, 2017; Hale et al., 2020; Doerr and Schaz, 2021). So far, the literature has shown that regulatory arbitrage opportunities can be an important driver of cross-border lending (Houston et al., 2012; Ongena et al., 2013; Karolyi and Taboada, 2015).[4] Our paper shows that heterogene-

[4]The impact of geographical and cultural proximity on cross-border lending is examined by Mian (2006);

ity in climate policy stringency among countries can also induce cross-border lending due to regulatory arbitrage opportunities it creates. This finding indicates that lack of homogeneity in the regulations for climate change can reduce the effectiveness of such regulations through a bank lending channel.

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 analyse if climate policy stringency affect bank lending decisions. Below, we describe data sources and how we constructed our sample. Table A1 reports a definition of all variables included in our analysis. Table 1 reports summary statistics of our sample.

Loan-level data We obtain loan-level data from LPC DealScan database. DealScan includes the most comprehensive loan-deal information on a global level. The unit of observation is a loan or facility, which is usually grouped into deals or packages. We gather data on bank loans with details on lender's share and name, loan maturity and amount, loan origination date, the name of borrowers, presence of collateral and covenants, name of the banks, among other characteristics. All loans are 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.[5] Finally, we split each loan into portions provided by syndicate members to

Lin et al. (2012).

[5]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 borrowing companies, we follow the literature and exclude borrowers with SIC between 6000 and 6999 from the sample.

obtain granular loan-level data. The time unit of observation is the year of loan origination.

We construct our dependent variable *Lender share* as the cross-border loan share within syndicate. We define cross-border lending as loans where the nationality of the parent bank is different from the nationality of the borrowing firm. DealScan contains full information on shares for each bank for about 27 percent of all loan portions included in the sample. We drop all observations for which there is a missing lender's share and for which we find an incorrect entry (lender share greater than 100 percent or equal to 0 percent, which corresponds to around 730 observations). We use actual shares as reported in DealScan in order to reduce the noise in the sample. The average value of cross-border loans' share is 7.71 percent with a standard deviation of 7.95.

Climate policy data Our main measure of climate policy is the Climate Change Performance Index (CCPI). The CCPI is an index developed by the non-governmental environmental and development organization Germanwatch e.V. to enhance transparency in countries' climate protection action (Burck et al., 2016).[6] The index, which is published on a annual basis, covers 57 countries and the European Union and takes values in the interval [0,100] (the higher the score the more stringent is the climate effort of the given country).[7] Specifically, the CCPI is based on fifteen measures classified into five categories: Greenhouse Gas (GHG) Emissions (60 percent), Renewable Energies (10 percent), Energy Efficiency (10 percent) and Climate Policy (20 percent).[8] The GHG Emissions category considers countries' emission levels and how they have been developed in the recent past; the Renewable Energies category assesses the share of renewable energies used by a country to achieve an effective

[6]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.

[7]The publicly available CCPI scores includes changes in the methodology of calculation applied by Germanwatch e.V. from 2013 onward. From the Germanwatch team we received a CCPI data set based on a uniform weightings for each index component, for which we are most grateful.

[8]80 percent of the measure is based on objective data; the remaining 20 percent on national and international climate policy is based on subjective assessments made from about 300 experts and non-governmental organisations from the respective countries.

emission reduction; the Energy Use category considers the reduction of energy use needed for products and services; finally, the Climate Policy component considers the international and national climate politics as well as all measures taken by national governments to reduce greenhouse gases.[9]

As argued by Delis et al. (2019), a measure for the stringency of country climate policy should account both for the ambition and the effort of the government policy itself. The former is measured by the efficiency of the policy, while the latter is measured by the effectiveness of the policy in reaching specific outcomes. Therefore, providing a complete picture of countries' climate protection action efforts, the CCPI has been employed by other studies to measure countries' climate policy stringency (Delis et al. 2019; Atanasova and Schwartz 2019; Lin et al. 2020).

After removing all observations for which we do not observe the CCPI scores of lenders' and borrowers' countries, we match the CCPI data to our loan-level data set. The average CCPI score value is 55.96 with a standard deviation of 8.29. Figure 1 shows the average value of CCPI score for each country included in our sample. The figure clearly shows that European countries have a climate policy that is on average more stringent compared to countries like Australia, Canada, Saudi Arabia, or United States. Scandinavian countries stand out in our sample. When we look at the improvement or progress made in terms of national climate policy over time (Figure 2), there is a clear heterogeneity in climate action efforts put forward by sample countries. Importantly, there is mismatch between average values and improvement in CCPI score, meaning that countries that improved in terms of climate policy stringency are not always part of the share of countries with high mean CCPI value.

[9]The data for the 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.

Bank-level data We obtain data on bank balance sheets by Bankscope and BankFocus.[10] Due to lack of common identifiers we hand-match banks in DealScan with financial information from Bankscope and BankFocus by bank name and country.[11] Prior to this match we process bank names in DealScan to account for name changes, mergers, and acquisitions over the sample period. To do so, we rely on merger and acquisitions information contained in Orbis Zephyr.[12] We link subsidiaries and branches for which balance sheet information is available in Bankscope and BankFocus to their parent financials, meaning that we do not treat them as separate entities. We do our hand-match exercise at consolidated level.[13] We are able to match a total of 1,056 parent banks (which corresponds to a total of 1,243 lenders in DealScan). As noted in De Haas and Van Horen (2013), subsidiaries typically do not participate in syndicated loans as the amounts involved are too large for their balance sheet, and therefore, funds are provided directly by the bank's headquarter. However, they are often involved by providing the parent bank with local information (De Haas and Van Horen, 2013). While we match 1,056 banks in total, our final sample of matched banks includes 294 parent banks located in 32 countries due to the availability of actual shares as reported in DealScan.

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 location (country, state, address, postal code). We identify the location of our sample banks using the country provided in

[10]The provider Bureau van Dijk has changed the name of the database Bankscope in BankFocus starting from year 2017. BankFocus contains data from 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 ongoing.

[11]We employ a fuzzy match exercise, or probabilistic record linkage, following Wasi and Flaaen (2015) in Stata.

[12]We are able to identify all deals in the sample period by matching Bankscope, BankFocus and Orbis Zephyr common BvD ID number. We follow the same procedure as in Hale et al. (2020). Specifically, we download information on all financial sector deals and keep only completed deals. We remove all deals for which acquiror and target names are not available. We also drop demergers - it amounts to 0.35%. We drop deal types such as minority and majority stake acquisition. We take deals starting from 2006.

[13]In cleaning and arranging our Bankscope-BankFocus data set, we follow the work by Duprey and Lé (2016) and the code kindly provided by the authors. We consider consolidated status of mother bank integrating the statements of its controlled subsidiaries or branches.

the Bankscope-BankFocus data set.

Firm-level data Data on firm financials come from Compustat/WRDS. We match borrowers in the DealScan loan-level sample to Compustat North America and Global databases following Chava and Roberts (2008). In particular, we use their DealScan-Compustat link table to match DealScan and Compustat borrower's identifiers.[14] We retain information on firm profitability, tangibility, size, leverage, and firm location. 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.[15] We merge data on borrower characteristics in the year of the loan origination. The regression data set a total of 1,387 firms located in 40 countries.

Country-level data Cross-border bank lending can be affected by economic, demographic conditions as well as by institutional quality, legal environment and cultural aspects shared with potential borrowers (Qian and Strahan, 2007; Giannetti and Yafeh, 2012). We deal with this concern by matching our loan-bank-firm sample with country-year variables gathered from the Worldwide Governance Indicators and from the IMF International Financial Statistics. In additional analyses, we control for economic and financial development which may affect the supply of credit including in our main specification GDP per capita and Domestic Credit to GDP ratio. We control for labor market development using unemployment rate, for the geographical closeness between borrowers and lenders by including the distance between lender's and borrower's country, and for cultural aspects by including sharing of common language with borrowers. We also control for demographic aspects via growth rate of population, the ratio of old as well as young dependents. We finally control for the importance of institutional quality and legal environment which we measure with creditor rights,

[14] The link table can be accessed through the following link: `http://finance.wharton.upenn.edu/~mrrobert/styled-9/styled-12/index.html`.

[15] 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.

property rights protection and number of days required to enforce a contract.

3 Empirical Approach

Our objective is to examine the relation between home country stringency of climate policy and cross-border bank lending. To do so, we estimate the following cross-country specification:

$$\text{Lender Share}_{\text{b,l,f,t}} = \alpha_{\text{l}} + \beta_1 \text{CCPI}_{\text{c,t-1}} + \beta_2 \mathbf{X}_{\text{b,l,t-1}} + \varepsilon_{\text{b,l,f,t}} \tag{1}$$

where Lender $\text{Share}_{\text{b,l,f,t}}$ is the dependent variable of interest, namely the cross-border loan share that bank b finances in foreign loan l to firm f in year t. The main regressor is $\text{CCPI}_{\text{c,t-1}}$ which measure the stringency of the climate policy of the country where the bank is located (hereafter lender-country) and which is indexed by c. Lagged values of the CCPI accounts for the fact that financing decisions may consider policies already implemented. $\mathbf{X}_{\text{b,l,t-1}}$ comprises 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). All controls are lagged in order to alleviate endogeneity concerns. α_l denote the vector of loan fixed effects and ε is the remainder disturbance. Finally, we estimate robust standard errors by double clustering at the lender's country-year level to account for serial correlation between each lender share of banks located in the same country overtime (Abadie et al., 2017). Note that we focus only on cross-border loan shares, meaning that banks and firms are located in different countries.

3.1 Threats to identification

In this section we discuss potential sources of endogeneity which may confound our estimates, and how we try to address them.

Disentangling loan demand from loan supply To estimate the relation between climate policy stringency and cross-border bank lending we should address the identification challenge of disentangling loan demand from loan supply. Due to the granularity of our data, we can address this challenge at different stages. First, we saturate the model with borrower, year, and borrower×year fixed effects at stages. The inclusion of borrower×year fixed effects allows us to control for all time-invariant and time-varying firm characteristics (such as profitability, investments, and balance sheet characteristics) which may affect the demand for credit (Khwaja and Mian, 2008). However, to mitigate the potential problem of banks joining loan syndicate due to loan characteristics (for example, loan type and purpose), we saturate Equation 1 with granular loan fixed effects. The inclusion of granular loan fixed effects saturate the model by controlling for unobserved and observed, time-variant and -invariant loan's, borrower's and borrower's country characteristics. Importantly, it controls for all demand-driven aspects that may confound our estimates. Therefore, in the most saturated version of our model, we can interpret the coefficient β_1 as capturing the effect of stringency of home country climate policy on cross-border loan supply.

Omitted variables Although we interpret our coefficient of interest as the effect of home country climate policy stringency on cross-border credit supply, bank's willingness to grant credit abroad may be affected by other aspects, such as markets' characteristics where the bank is operating or aspects shared with borrowing firms. For example, a bank can decide to join the syndicate and finance a loan share to a foreign firm for reasons related to that aspects make it inconvenient to grant credit domestically, for example home country economic development.

To further rule out potentially confounding factors, we examine the sensitivity of our results to controlling for all country-level aspects that have been shown to affect the cross-border credit supply (Qian and Strahan 2007; Giannetti and Yafeh 2012; Houston et al. 2012; Karolyi and Taboada 2015). Specifically, we control for quality of institutions, cultural aspects shared between lenders and borrowers (common spoken language), geographic distance between lenders and borrowing firms, and country's demographic and macroeconomic characteristics. We report results of this additional exercise in section 4.2.

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 and use granular fixed effects to control for loan demand and a rich set of control variables to mitigate concerns related with omitted variable bias. In Section 4.2 we exploit heterogeneity at the lender level to document the mechanism. We conclude this section with an analysis about how the effect changes with respect to the components of the CCPI.

Before moving to the regression models, Figure 3 plots a strong and positive correlation between the CCPI and cross-border loans share at the bank balance sheets. Even though, this plots provides evidence for how banks use cross-border lending to react to higher climate policy stringency, it can be driven by some other factors such as loan demand and variables that are correlated with both the 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.

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 explained in section 3, one of the concerns with such model is that loan demand can be correlated with the CCPI. For instance, observing an increase in the CCPI of a country, the borrower may decide to increase its demand to the lenders from that country. The reason might that having a lending relationship with lender from a high CCPI country can generate a positive signal for the borrower. Or, 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 with loan demand, we use granular fixed effects to control for borrower characteristics and report the results in Table 2. In Column (1), we start with borrower fixed effects and lender level control variables, such as log(total assets), capital ratio, liquidity ratio. 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 U.S.A. has experienced between 2007 and 2017. In Column(2), we include year fixed effects to control for time effects. In Column (3), we saturate the model with borrower $\times$year fixed effects, which implies that we compare loan shares of different lenders for the same borrower at the same time. Under the assumption that loan demand is constant across the lenders, this within-firm estimator controls for loan demand (Khwaja and Mian, 2008). The magnitude of the estimated coefficient stays stable across these models, which implies that the positive relationship between cross-border loan supply and climate policy stringency is not driven by loan demand.

Another concern regarding the model in Equation 1 could be that loan terms can be correlated with both the CCPI and loan shares. Therefore, not controlling for loan terms can introduce a bias into our estimations. The granularity of syndicated loan data allows us to take a step further and include loan fixed effects into the regression model. Column (4) reports the results of the model with the loan fixed effects. In this most saturated model, we compare two lenders of the loan and hold the effects of loan terms constant. The magnitude of the CCPI in this model is remarkably similar to ones in the previous models, which mitigates the concerns about loan terms and loan demand.

Being a weighted average of 14 different climate policy related measures, the CCPI can be correlated with other country level variables. For instance, an improvement in the economic conditions can allow residents of the country to be more careful about the environment, which can lead to a higher CCPI score. Or, cultural differences among the countries can generate heterogeneity in the CCPI.[16] In addition, changes in the demographics of a country might have an influence on climate change awareness – a younger population can be more careful about the environment. Moreover, legal conditions of the country can be reflected on the CCPI as the CCPI also covers legal actions against the climate change. All of these variables can pose a threat for our estimations to the extent that they are correlated with loan supply.

To mitigate concerns about omitted variables, we collect variables on the conditions of the lender's home country and include these variables into our models. More specifically, in Column (1) of Table 3, we include log(GDP per capita), domestic credit to GDP ratio, unemployment rate to control for economic conditions of the lender's home country. To control for cultural aspects, we include a dummy variable that takes the value of 1 if lender and borrower country have the same language and log of distance between these countries to control for cultural heterogeneity in Column (2). We use population growth, share of old and young workforce in Column (3) to control demographics. Finally, we follow the literature and include indices for credit and property rights with 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 the CCPI survives and its magnitude is similar to the ones we have in Table 2. These results indicate that the positive relation between climate policy stringency of bank's country and bank's cross-border lending is not driven by loan demand or other variables.

[16] Results from Round 8 of the European Social Survey shows that there is cross-national variation in climate preferences and beliefs - for example, 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).

4.2 Additional analysis

In this section, we provide additional evidence on the increase in cross-border lending as a reaction to higher climate policy stringency. The mechanism we propose is that banks use cross-border loans to avoid the implications of climate policies on their loan portfolios. If this is the underlying mechanism, then the positive relationship between cross-border lending and the CCPI should exist only if the lender's home country CCPI is higher than borrower's home country CCPI. The reason is that if borrower is exposed to a more stringent climate policy, increasing loan supply to such borrowers would not lower CCPI exposure of bank's loan portfolio. In line with this intuition, Table 4 documents that the positive association between cross-border lending and the CCPI occurs only if the lender's home country has a higher CCPI than the borrower's home country. When lender's home country has a lower CCPI than the borrower's home country, the magnitude of the CCPI's coefficient is statistically and economically insignificant, which lends additional support to our proposed mechanism.

We continue to our analysis by exploring how the effect differentiates with respect to the lender characteristics. In Columns (1) and (2) of Table 5, we split our sample in terms of bank size. For larger banks, increasing the 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 is less important. In line with this intuition, we find that the increase in cross-border lending is stronger for larger banks. Similarly, for banks that have 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 us in Columns (3) and (4) of Table 5. The increase in lender share is four times larger for the banks whose cross-border loans ratios above the median of our sample. Moreover, we also find that the effect is stronger for less capitalized banks, which is in line with literature that documents the relationship between risk-taking and bank capital (Holmstrom and Tirole, 1997; Ongena et al., 2013; Jiménez et al., 2014). In the last two columns of Table 5, we divide our sample into two subsamples with respect to the banks' NPL ratio. If the driving mechanism for the positive association between climate policy stringency and cross-border lending is banks' concern about how their loan portfolio would be affected by these policies, then the effect should be stronger for the banks with 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. We confirm that indeed this is the case.

In the last part of this section, we investigate which parts of the CCPI are more important for the increase in cross-border lending. The CCPI has four parts: "GHG Emission", "Renewable Energy", "Energy Use", and "Climate Policy." For each part, an increase in the value represents more environment friendly policy (Burck et al., 2016). In a nutshell, as the names suggest, GHG Emission shows countries' greenhouse gas emissions, Renewable Energy shows how much the countries substitute their fossil energy with renewable energy. Energy Use is about countries' energy efficiency. Lastly, Climate Policy measures the actions that the countries take to reduce greenhouse emissions both at national and international level.

We take these four groups and run horse-race regression models in Table 6. Similar to Table 2, we start with borrower fixed effects and bank controls in Column (1). Then, we saturate the model with year, borrower × year, and loan fixed effects respectively. In all of these 4 models, only the coefficient of Climate Policy has consistently positive and significant effect. This finding indicates that banks react to policies about climate change instead of realized outcomes of such policies. Moreover, this finding also supports the interpretation that banks use cross-border lending as a regulatory arbitrage opportunity.

5 Conclusion

In this paper we investigate whether banks use cross-border lending to react to a change in climate policy stringency in their home country. Specifically, we study the link between the cross-border credit supply and the stringency of bank home country climate policy using as laboratory of analysis the syndicated loan market. Indeed, costs stemming from new climate regulation may incentivise banks to take advantage of cross-country differences in climate policy and lend more to foreign firms located in lax climate policy countries. This conjecture is well supported by the literature and by recent empirical findings (De Haas and Popov, 2019; Krueger et al., 2020; Bartram et al., 2021).

We find evidence that banks located in countries with stringent climate policy increase their cross-border credit supply to firms located in countries with weak climate performance. We saturate our specification with loan fixed effects which allow us to isolate the credit supply from credit demand, and to control for (un)observed loan and firm characteristics which may affect the lending decision. Results show that a one standard deviation increase in bank's home country climate policy is associated with their cross-border loan share by 0.41 percent. To mitigate omitted variable bias concerns, we check for the robustness of our results by additionally controlling for lender's country quality of institutions, legal environment, demographic, economic aspects and for cultural aspects shared with borrowing firms. This effect is stronger for big, less capitalized banks as well as for banks that are more experienced in the syndicated loan market. We also find that the effect is stronger for banks that have low bank lending standards, namely those that that face a higher nonperforming loans ratio (NPL).

The findings of this paper aims at helping the discussion on how policymakers can better identify the recipients of their climate regulation in an environment where lack of policy harmonization might triggers regulatory arbitrage behavior and threaten the effectiveness of climate policies.

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Figures and Tables

Figure 1: **Average climate policy.**

This map reports the average Climate Change Performance Index (CCPI) score per each country included in our sample over sample period 2007-2017. The shade in color proxies the average value - darker areas indicate higher average values (more stringent climate policy). Average values in CCPI scores are: Australia (33.82), Austria (48.84), Belgium (56.76), Brazil (59.07), Canada (32.71), China (53.16), Chinese Taipei (43.39), Denmark (64.24), France (54.64), Germany (62.86), Greece (47.66), India (57.45), Indonesia (55.83), Ireland (48.85), Italy (51.56), Japan (48.50), Korea (47.90), Malaysia (44.30), Netherlands (52.86), Norway (57.76), Portugal (65.61), Russian Federation (47.59), Saudi Arabia (39.16), Singapore (52.13), South Africa (49.42), Spain (49.60), Sweden (60.27), Switzerland (59.94), Thailand (57.03), Turkey (52.49), United Kingdom (60.95), United States (31.29). Countries with no color shade are not part of our sample.

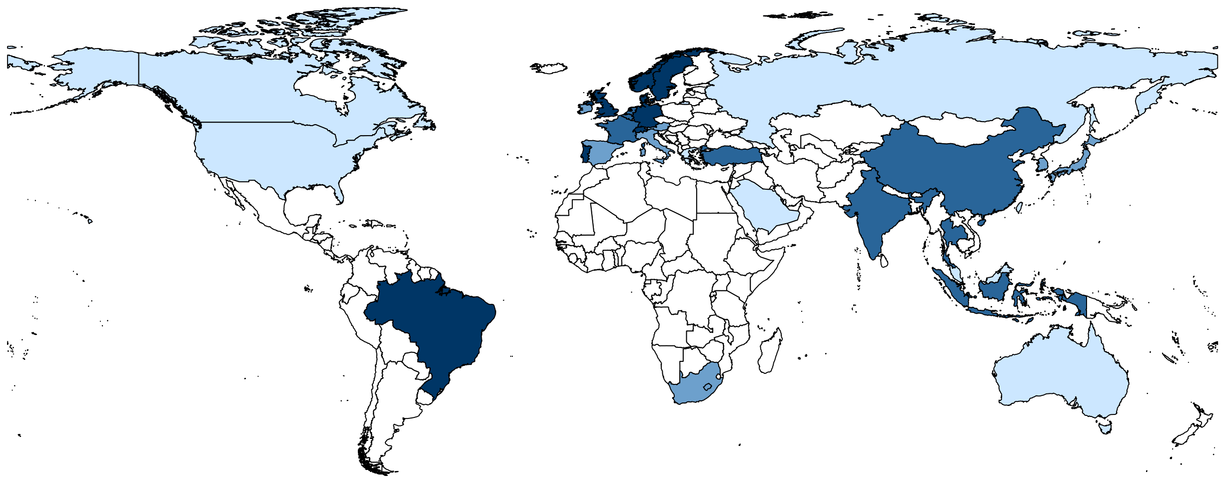

Figure 2: **Progress in climate policy.**

This map reports the progress made in national climate policy by each country included in our sample. We calculate progress in climate policy as the difference between the maximum and minimum Climate Change Performance Index (CCPI) score achieved by each country over sample period 2007-2017. The shade in color proxies the progress made - darker areas indicate higher differences values (more progress). Differences between max and min CCPI scores are: Australia (11.07), Austria (9.60), Belgium (12.28), Brazil (12.55), Canada (10.33), China (10.73), Chinese Taipei (2.77), Denmark (25.29), France (11.52), Germany (11.65), Greece (10.14), India (11.40), Indonesia (6.28), Ireland (13.77), Italy (16.72), Japan (13.54), Korea (11.17), Malaysia (5.62), Netherlands (12.64), Norway (12.00), Portugal (5.52), Russian Federation (3.27), Saudi Arabia (16.32), Singapore (12.29), South Africa (10.06), Spain (9.72), Sweden (10.19), Switzerland (1.80), Thailand (9.61), Turkey (5.43), United Kingdom (11.64), United States (24.18). Countries with no color shade are not part of our sample.

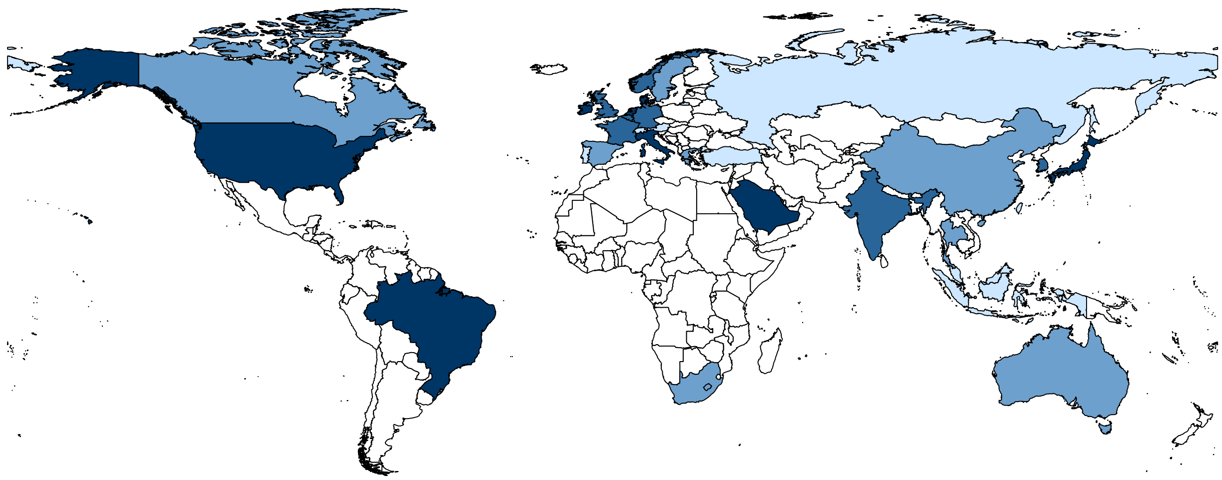

Figure 3: **Home country climate policy and cross-border bank lending.**

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 in percentage values by sample banks. The CCPI score takes values in the interval [0;100], where higher values proxy a country with more stringent climate policy. The panel consists of 38 countries over the period 2007-2017. The share of cross-border lending in total lending is calculated using information on banks balance sheets. Specifically, it is calculated as the ratio between 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. The regression controls for parent banks and year fixed effects. For variable definitions, see Table A1.

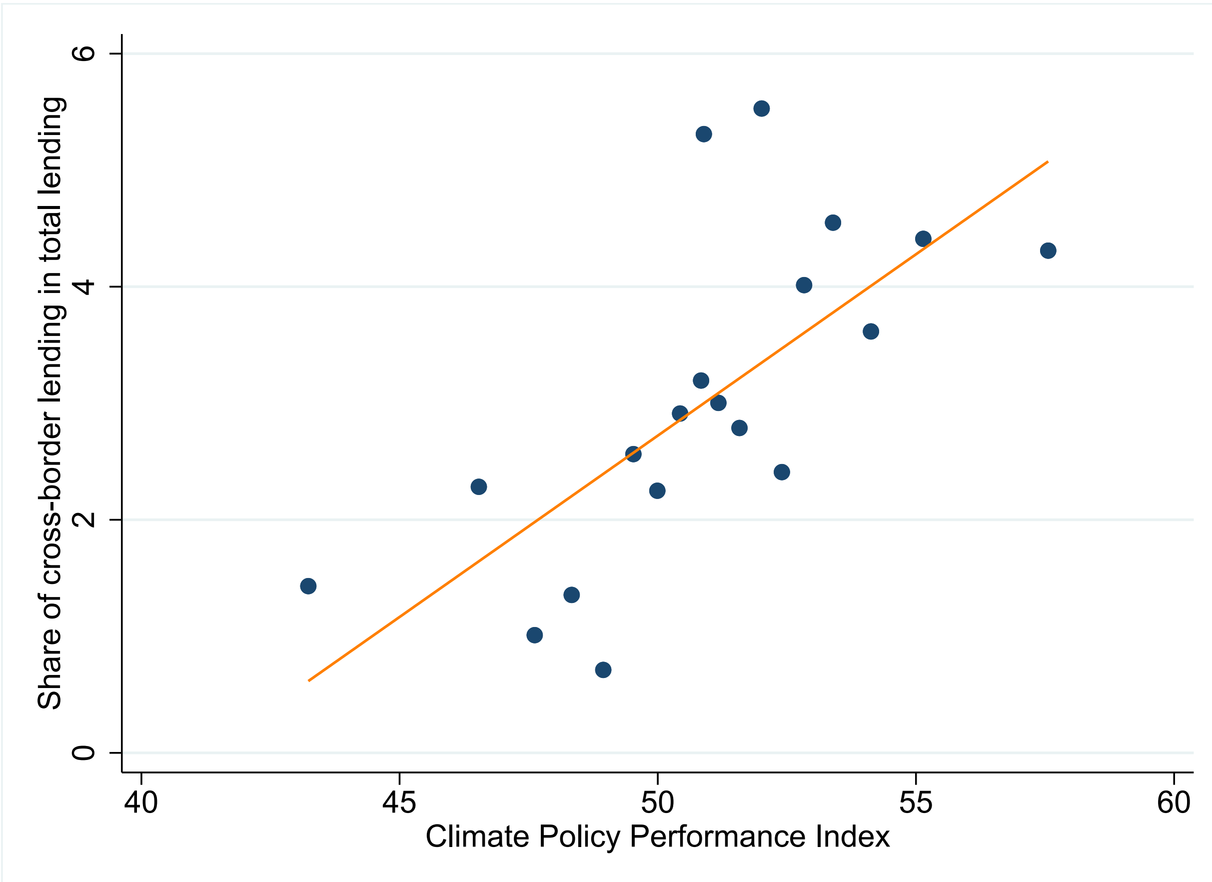

Table 1: **Summary statistics**

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. For variable definitions, see Table A1.

	Obs.	Mean	Std. Dev.	Min.	Max.
Lender share	12,500	7.713	7.952	0.070	94.210
$CCPI_{lender}$	12,500	55.961	8.291	22.848	76.620
log(Total assets)	12,500	27.738	3.806	10.635	36.821
Tier 1 capital ratio	12,500	12.332	8.139	3.700	432.600
log(Customer deposits)	12,500	26.902	3.995	6.639	36.705
Liquidity ratio	12,500	49.126	35.746	0.720	395.494
ROAE	12,500	5.708	11.387	-223.690	46.090
Net interest margin	12,500	1.484	0.801	-0.345	9.170
log(GDP per capita)	11,971	10.468	0.706	6.906	11.571
Domestic credit to GDP	11,710	119.357	35.421	25.456	206.671
Unemployment rate	11,971	7.840	3.787	0.576	27.071
Common Language	11,553	0.248	0.432	0	1
log(Distance)	11,553	7.907	1.023	4.922	9.384
Creditor rights	8,183	65.492	21.997	30	100
Property rights	11,898	76.697	18.483	20.000	97.100
log(Contract enforcing days)	6,712	4.617	0.509	3.258	5.720
Population growth	11,971	0.531	0.540	-1.854	5.322
Old workforce	11,971	26.045	6.601	4.192	45.125
Young workforce	11,971	26.338	4.383	15.767	55.337
Climate $policy_{lender}$	12,500	11.957	4.367	0	20
Renewable $energy_{lender}$	12,500	2.606	1.711	0.023	8.094
Energy use_{lender}	12,500	5.768	1.488	1.017	9.124
$CO_{2lender}$	11,705	35.613	5.420	9.570	45.564

Table 2: **Climate policy and 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. At stages: column (1) reports estimates when controlling for borrower fixed effects; column (2) when controlling for time fixed effects; column (3) when controlling for borrower-time fixed effects; column (4) reports estimates from our preferred version of the main specification, namely when we saturate the model with loan fixed effects. All regressions include bank-level controls (Net Interest Margin, Tier 1 Capital Ratio, log(Total Assets), log(Customer deposits), Liquidity ratio). The lower part of the table denotes the type of fixed effects used in each specification. Robust standard errors are double clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share			
	(1)	(2)	(3)	(4)
CCPI_{lender}	0.031***	0.032***	0.034***	0.031***
	(0.008)	(0.009)	(0.008)	(0.008)
Controls & Fixed Effects:				
Bank Controls	✓	✓	✓	✓
Borrower FE	✓	✓		
Year FE		✓		
Borrower × Year FE			✓	
Loan FE				✓
Obs.	12,500	12,500	12,500	12,500
R^2	0.732	0.733	0.806	0.841
Mean(Lender Share)	7.713			

Table 3: **Controlling for quality of institutions, legal environment, cultural aspects, and country characteristics.**

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. We control at stages for countries' macroeconomic conditions, cultural aspects, quality of institutions and legal environment, and for demographic characteristics. The lower part of the table denotes the type of fixed effects used in each specification. All regressions include bank-level controls (Net Interest Margin, Tier 1 Capital Ratio, log(Total Assets), log(Customer deposits), Liquidity ratio). Robust standard errors are double clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share			
	(1)	(2)	(3)	(4)
CCPI_{lender}	0.029***	0.021**	0.021**	0.036**
	(0.009)	(0.008)	(0.009)	(0.014)
Controls & Fixed Effects:				
log(GDP per capita)	0.438***	0.400***	0.491***	-0.254
	(0.090)	(0.080)	(0.117)	(0.528)
Domestic credit to GDP	0.005***	0.006***	0.006***	0.004
	(0.001)	(0.001)	(0.002)	(0.006)
Unemployment rate	-0.011	-0.007	-0.006	0.043*
	(0.013)	(0.011)	(0.012)	(0.025)
Common Language		-0.026	0.017	0.202
		(0.149)	(0.151)	(0.321)
log(Distance)		-0.196**	-0.191**	-0.271
		(0.089)	(0.092)	(0.224)
Population growth			-0.174*	0.590
			(0.094)	(0.444)
Old workforce			-0.017	-0.010
			(0.018)	(0.040)
Young workforce			-0.002	-0.033
			(0.014)	(0.035)
Creditor rights				-0.010
				(0.010)
Property rights				0.004
				(0.025)
log(Contract enforcing days)				-1.032**
				(0.500)
Bank Controls	✓	✓	✓	✓
Loan FE	✓	✓	✓	✓
Obs.	11,572	11,113	11,113	2,915
R^2	0.850	0.853	0.853	0.879
Mean(Lender Share)	7.713			

Table 4: **Climate policy and cross-border lending: controlling for borrower's country climate policy stringency.**

This table reports estimates from Equation 1. The dependent variable is *Lender share* and the main independent variable is $CCPI_{lender}$. The sample covers the period 2007-2017. Specifically, columns (1) to (4) shows results when we split the sample in cases where the CCPI Index of the lender's country is higher/lower than the one of the borrower's country. The lower part of the table denotes the type of fixed effects used in each specification. All regressions include bank-level controls (Net Interest Margin, Tier 1 Capital Ratio, log(Total Assets), log(Customer deposits), Liquidity ratio). Robust standard errors are double clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	$CCPI_{borrower} < CCPI_{lender}$			
	(1)	(2)	(3)	(4)
	Yes	No	Yes	No
$CCPI_{lender}$	0.056***	0.008	0.053***	0.006
	(0.014)	(0.014)	(0.015)	(0.015)
Controls & Fixed Effects:				
Bank Controls	✓	✓	✓	✓
Borrower × Year FE	✓	✓		
Loan FE			✓	✓
Obs.	8,503	3,444	8,350	3,165
R^2	0.807	0.820	0.850	0.843
Mean(Lender Share)	7.713			

Table 5: **Climate policy, cross-border lending, and 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. Specifically, columns (1) and (2) show results when we differentiate between banks that have total assets above/below sample median level (Size). Columns (3) and (4) show results when we differentiate between banks that have an aggregate amount of cross-border lending in total lending that is above/below sample median level (Cross-border). In columns (5) and (6), we report results when we differentiate between banks that have Tier 1 capital ratio above/below sample median levels (Capital). Finally, columns (7) and (8) show results when we differentiate between banks that have lending standards above/below sample median level (Nonperforming loans). The lower part of the table denotes the type of fixed effects used in each specification. Robust standard errors are double clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

Lender Share	Size		Cross-Border		Capital		NPL	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Low	High	Low	High	Low	High
$CCPI_{lender}$	0.018**	0.056***	0.021**	0.089***	0.055***	0.032***	-0.041	0.102***
	(0.008)	(0.015)	(0.010)	(0.019)	(0.011)	(0.012)	(0.028)	(0.027)
Controls & Fixed Effects:								
Loan FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	5,135	5,525	4,904	6,032	5,579	5,434	750	1,015
R^2	0.848	0.844	0.833	0.848	0.841	0.854	0.836	0.778
Mean(Lender Share)	7.713							

Table 6: **Which component of CCPI is more important?**

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. At stages: column (1) reports estimates when controlling for borrower fixed effects; column (2) when controlling for time fixed effects; column (3) when controlling for borrower-time fixed effects; column (4) reports estimates from our preferred version of the main specification. The lower part of the table denotes the type of fixed effects used in each specification. All regressions include bank-level controls (Net Interest Margin, Tier 1 Capital Ratio, log(Total Assets), log(Customer deposits), Liquidity ratio). Robust standard errors are double clustered at the lender's country-year level and shown in parentheses. For variable definitions, see Table A1. *** p<0.01, ** p<0.05, * p<0.1.

	Lender Share			
	(1)	(2)	(3)	(4)
Climate policy$_{lender}$	0.031**	0.026*	0.036***	0.029**
	(0.015)	(0.015)	(0.013)	(0.014)
Renewable energy$_{lender}$	-0.018	0.043	0.003	0.039
	(0.037)	(0.050)	(0.047)	(0.048)
Energy use$_{lender}$	0.012	0.115	0.016	0.025
	(0.056)	(0.084)	(0.076)	(0.079)
$CO_{2lender}$	0.038**	0.013	0.036*	0.027
	(0.017)	(0.022)	(0.020)	(0.021)
<u>Controls & Fixed Effects:</u>				
Bank Controls	✓	✓	✓	✓
Borrower FE	✓	✓		
Year FE		✓		
Borrower × Year FE			✓	
Loan FE				✓
Obs.	11,705	11,705	11,705	11,705
R^2	0.743	0.743	0.811	0.847
Mean(Lender Share)	7.713			

Table A1: **Variables definition and sources.**

Variable name	Variable definition	Source
Lender share (%)	Cross-border loan share in % values financed by syndicated loan participants.	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-BankFocus
Net Interest Margin (%)	Percentage of earnings in interest as compared to the outgoing expenditures payed to customers.	Bankscope-BankFocus
Customer deposits (log)	Total customer deposits in USD millions.	Bankscope-BankFocus
Nonperforming loans (NPL) (%)	Ratio of loans defined to be nonperforming over gross loans in USD millions.	Bankscope-BankFocus
Liquidity ratio (%)	Ratio of liquid assets over deposits and short-term funding.	Bankscope-BankFocus
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 equals to one if the two countries share the same language.	Rose (2004)
Distance (log)	Log of geographic distance between borrower's and lender's country.	Rose (2004)
Creditor rights	Strength of legal rights index, which ranges from 0 to 100, measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. Higher scores indicate that these laws are better designed to expand access to credit.	World Bank
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