Climate Risk and Cross–Border Lending: Evidence from the Syndicated Loan Market

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María José Arteaga Garavito* Deniz Igan† Jakub Demski‡ Koji Takahashi§

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Abstract

This paper explores to what extent climate risk is reflected in cross-border lending decisions in the syndicated loan market. We construct a climate risk index for a wide range of countries using major newspapers' posts on Twitter. We find that when risk in climate news increases in a lender's home country, their engagement in cross-border lending to firms in brown sectors increases. Our results suggest that lenders evaluate the climate risks at home and borrowers' country when they allocate credits across countries. Furthermore, the effect is more pronounced for lenders who have a higher exposure to firms in brown sectors.

Keywords: Syndicated loans, climate risks, tweets, social media, text analysis, credit supply
JEL Classification codes: G21, G23, Q50, D8

*Bocconi University. Email: maria.arteaga@phd.unibocconi.it
†Bank for International Settlements and CEPR. Email: deniz.igan@bis.org
‡Bank for International Settlements. Email: jakub.demski@bis.org¿
§Bank of Japan. Email: kouji.takahashi-2@boj.or.jp

1 Introduction

As the impacts of climate change become increasingly apparent, the ongoing global debate over associated risks and potential mitigation strategies continues to intensify. This conversation goes beyond borders, highlighting the collective goal of many nations to reach zero greenhouse gas emissions. However, the journey to zero emissions is complex, influenced by varying public perspectives on climate risks over time and across different regions. Against this backdrop, the financial system is under heightened pressure to play a pivotal role in supporting, if not accelerating, the transition to a green economy. Notably, large corporations significantly contribute to greenhouse gas emissions due to their higher production levels, more extensive operations, and broader geographical reach. These corporations often rely on the syndicated loan market for funding. And the role of cross-border lending has increased (Figure 1). Hence, understanding the intricate connection between the cross-border lending market and climate risks is crucial for evaluating the progress towards reduced or zero-emission objectives.

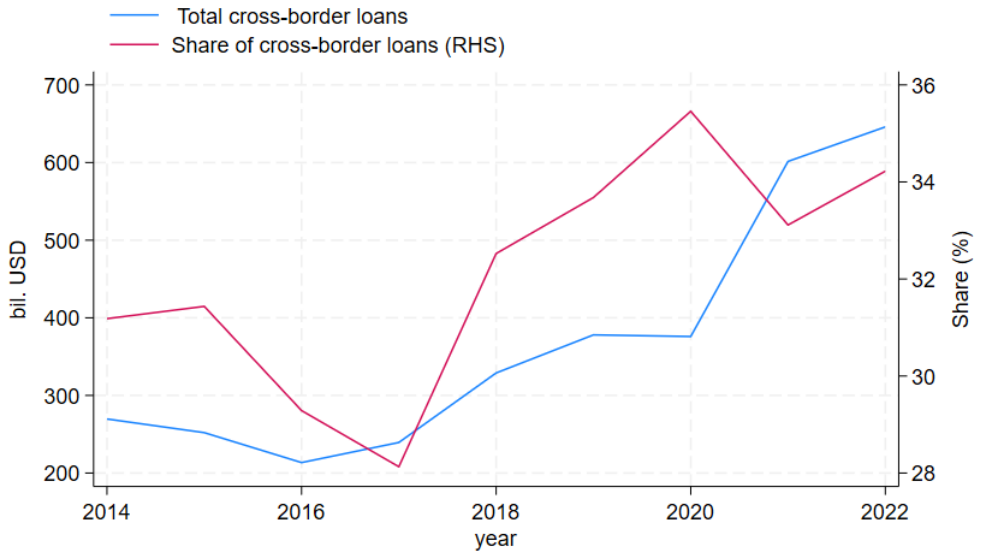

Figure 1: Cross-border syndicated loans

Source: Dealogic

In this paper, we investigate the impact of climate risk on cross-border lending in the context of the global syndicated loan market. Our approach involves constructing a Climate Risk Index (CRI) by analyzing social media posts on Twitter from major newspapers for a wide set of countries. Our index defines climate risk as the number of posts that mention *climate change* or *global warming* as a share of the universe of posts and simultaneously mention risk and policy. Through this attention index, we are able to capture the public attention given to climate

matters and its influence on cross-border loan allocation.

ADD HERE MORE ON THE SELECtion OF SYNDICATED LOANS

Given the broad focus of our index, capturing not only physical risks (e.g., droughts) but also transition risks (e.g., COP meetings), it serves as a proxy for the uncertainty surrounding climate change. We anticipate that an increase in climate news attention in the home country of lenders would lead to an expansion of cross-border loans, as lenders prefer countries with lower climate risks. Conversely, a surge in climate attention within a borrower's country is expected to deter loans from foreign lenders. Our analysis delves into these dynamics, offering insights into the relationship between climate news attention and the allocation of cross-border loans.

ADD HERE MORE ON THE empirical strategy // not controlling for loan-demand directly

In our baseline model, we measure the impact of climate attention in the home country of the borrower in the syndicated loan agreement. After controlling for various country characteristics, our analysis reveals a consistently negative impact across different specifications. Furthermore, we extend our baseline model and measure the impact of climate attention changes in the lender's country, observing a nuanced relationship between lender-country *CAI* and cross-border lending, especially concerning firms from brown sectors. Robustness checks, including deal-level fixed effects, strengthen our findings. Additionally, we explore the disparity in *CAI* between lender and borrower countries, shedding light on how this difference affects cross-border lending dynamics. Consistent with our baseline results, we show that an increase in the relative attention in the lender country would increase the cross-border allocation of resources.

Our contribution is twofold. First, we develop a novel climate news attention index for a wide set of countries, which allows us to compare allocation effects through cross-border lending. Second, we present new evidence that lenders consider not only current climate policies but also climate risks, including the possibility of future stringent policies, when allocating resources between borrower countries.

Related literature. Overall, our study contributes to the growing body of literature on the intersection of climate change and finance. Specifically, recent research has focused on the effect of climate change on syndicated loan characteristics. Kacperczyk and Peydró (2022) study syndicated lending decisions by banks in the presence of green pledges. Ehlers et al. (2022) combines syndicated loan data with carbon intensity data and find evidence of a risk premium charged to borrowing firms with higher carbon intensities post-Paris Agreement. Similarly, Ho and Wong (2023) examines the impact of firm-level carbon emissions on the terms of syndicated loans originating from emerging markets. They find that green banks charge higher loan spreads when lending to the same brown firm in the post-Paris Agreement period. Degryse et al. (2023)

finds that green banks reward firms for being green in the form of cheaper loans but only after the ratification of the Paris Agreement. While most of these studies utilize a policy stringency index as a variable of interest or control, our approach differs as we primarily focus on climate attention, which encompasses both policy and public attention. Mueller and Sfrappini (2022) also studies how firms' risks of climate-related regulations affect banks' lending behavior using the Paris agreement as a regulatory shock. They find that in the United States, banks increase loans to firms that are more likely to be negatively affected by the regulations while banks lend more to European firms that benefit more from regulation. Altavilla et al. (2024) find that banks in the Euro area charge higher interest rates to firms with greater carbon emissions and offer lower rates to those committed to reducing emissions. This behavior is more pronounced among banks dedicated to decarbonization, indicating a climate risk-taking channel in lending policies. In addition, Meisenzahl (2023) conclude that since 2012, major U.S. banks have significantly reduced lending to regions more affected by climate change, particularly after 2015. This suggests a strategic shift in loan portfolios to mitigate exposure to climate-related risks. On the other hand, Giannetti et al. (2023) reveals that banks emphasizing environmental issues in their disclosures tend to lend more to brown industries and to borrowers with higher emissions. This finding suggests a potential disconnect between banks' environmental communications and their actual lending behaviors. Furthermore, Sastry et al. (2024) find that climate-aligned banks do not change their lending or loan pricing differentially compared to banks without climate commitments, suggesting they are not actively divesting.

Closest to our work, Benincasa et al. (2022) investigates how banks' cross-border lending responds to changes in climate policy stringency in their home countries. Similar to our approach, the authors utilize syndicated loan data to investigate the effect of stringency of climate policy in the lender's country and find that lenders with more stringent policy increase cross-border loans. We differ from Benincasa et al. (2022) in several ways. While Benincasa et al. (2022) primarily explored the effect of policy stringency measured by the Climate Change Performance Index (CCPI), our study takes a complementary approach by examining the impact of attention to climate, encompassing both policy and public attention. We control for the effect of climate policy stringency with the same index and find consistent results. This highlights the importance of public attention and the role it might play on cross-border funding decisions.

2 Data

Our loan-level data comes from Dealogic, which includes information on syndicated loans originated by multiple banks and non-banks. We focus on cross-border deals between lenders and

non-financial firms signed between 2014 and 2022. Dealogic offers information at the tranche level, including borrower and lender's name and nationality, lenders' role in the syndicate (e.g., bookrunner or participant), type of loan (e.g., revolving credit), maturity date, among others. The dataset also offers some insight on the structure of holding companies by stating the parent entity and its nationality. We match Dealogic data with ORBIS Bureau van Dijk's database in order to collect information at the firm-level.[1] Furthermore, we match both the lender and its parent's name with BankFocus and ORBIS databases to collect information at the lender-level.[2] Table A1 summarizes the definition of our loan-, firm-, bank- and country-level variables.

2.1 Loan allocation

As it is well noted in previous studies, lender shares from a syndicate at origination are not usually reported.[3] Some studies fill in the missing values by assuming distributions based on estimates of private data (Blickle et al. (2022)) or assuming an equally distributed share amongst participants (Fatica et al. (2021)). In our baseline results, we follow previous literature (Ivashina and Scharfstein (2010)) and assume that the distribution among lead and non-lead banks is the same between the observed and unobserved deals. More specifically, following Dealogic's guidelines, we define a lead bank in a syndicate as the designated bookrunner or the mandated lead arranger. In the cases where neither is found, the administrative agent, arranger, syndication agent, documentation agent, facility agent or participant would be considered as the lead bank (in that order). We however distinguish between the size of the syndicate (see Figure A1), and match the average allocation between lead and non-lead banks. If there are more than one bank in either category, then we equally allocate the group share. This disaggregation allows us to have a lender-borrower-tranche-level database.

2.2 Climate policy indexes

To measure a country's climate attention, we develop three distinct indexes: (1) raw attention to climate, (2) climate policy attention, and (3) climate *risk* policy attention. These indexes are constructed using Twitter posts sourced from major newspapers in 17 countries. In the spirit of Arteaga et al. (2023), our data collection spans from October 2014 to December 2022, leveraging

[1] Dealogic and ORBIS databases do not share common identifiers for lenders and borrowers. Therefore, we use a batch search approach by relying on the companies' name and nationality. We are able to successfully match approximately 80% of companies.

[2] Lenders in Dealogic include both banks and non-banks. Therefore, the match to BankFocus is not generally successful to populate lender characteristic variables. ORBIS includes information on both banks and non-banks, so we complement lender identifiers and characteristics from ORBIS.

[3] Dealogic offers information on loan allocation to each bank parent company in a tranche for approximately 20% of tranches.

Twitter's API to recover posts from newspapers selected based on their circulation importance and active presence on Twitter (Table A2 in the Appendix summarizes the sources used). In a first step, we calculate the number of posts (raw count) which mention: (1) climate change or global warming[4]; (2) both climate- and policy-related keywords; and (3) simultaneous mention of climate-, policy and risk-related keywords. Table 1 summarizes the relevant keywords related to *policy* and *risk*.[5] In a second step, and to adequately account for newspapers' volume, we standardize our time series of raw counts following Baker et al. (2016).We follow a three-step approach: (1) standardize each monthly newspaper-level series to a standard deviation equal to 1; (2) average across newspapers for each month; and (3) normalize the series to a mean of 100. Table 2 shows descriptive statistics for the climate policy standardized index.

Figure 2 shows the simple average for the 17 countries in our sample. We highlight an increase in climate policy attention and risk during significant events, such as the Paris Agreement in end-2015 and publish dates of UN reports on climate change.

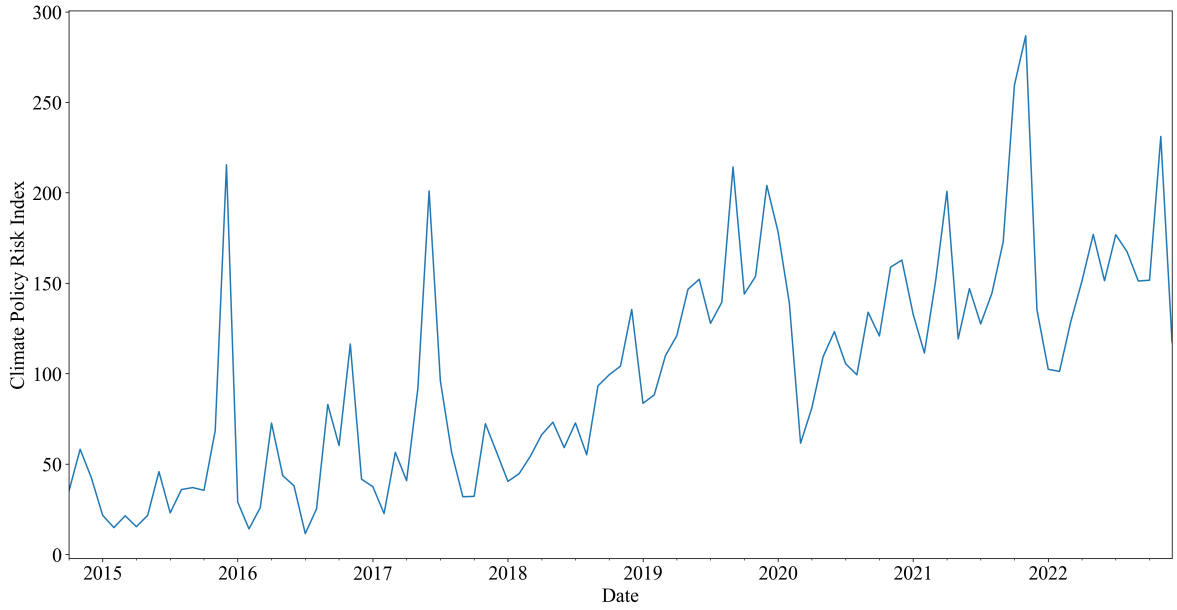

Figure 2: Climate policy indexes - monthly frequency

Note: This figure displays the simple monthly average for our of climate policy indexes. It shows the simple average for three climate attention indexes: (1) raw climate change attention; (2) climate policy attention; and (3) climate policy risk attention. Methodology is explained in Section 3.2. The correlation between the three averaged indexes ranges from 0.82 to 0.91. The sample spans from October 2014 to December 2022 and includes data from 17 countries.

[4]We address the diverse expressions of climate-related discourse inherent in Twitter text, identifying climate-related tweets through mentions of phrases like "climate change" or "#climatechange."

[5]Following Ardia et al. (2023), we sourced risk-related terms from the Linguistic Inquiry and Word Count (LIWC2015) lexicon.

Table 1: Policy and Risk Related Terms

Policy related terms		
policy	guidelines	governance
decision	deregulation	policymaker
legislative	principles	administration
enforcement	legislation	jurisdiction
government	regulatory	statutory
agreement	monitoring	framework
regulation	rules	implementation
regulate	measures	intervention
compliance	law	oversight
act	tax	reform

Risk related terms					
abstain	dangerous	fled	loses	suppress	wrong
alarm	dangerously	flee	losing	tentativ	yield
apprehens	dangers	fleeing	loss	threat	uncertain
averse	defend	flunk	pessimis	troubl	uncertainly
aversi	defense	hide	prevent	trust	uncertainties
avert	difficult	guard	problem	trusted	uncertainty
avoid	difficulties	hazard	protect	trusting	
bad	difficulty	hide	refrain	trusts	
balk	disadvantag	hesita	reluctan	trustworthiness	
beware	disaster	hiding	risk	trustworthy	
careful	distrust	hid	safe	undesir	
caution	doom	hinder	safely	unproduc	
cautious	doubt	lack	safety	unprotected	
cease	dread	lacked	secur	unsure	
concern	escap	lacking	stop	unwanted	
consequen	evad	liabilit	stopping	vigilan	
crises	expense	lose	stops	warn	
crisis	expenses	loses	stopped	worse	
curb	fail	loss		worst	

Additionally, we supplement our analysis with other indices. First, the Climate Change Performance Index (CCPI) by Germanwatch, which tracks the climate protection performance of various countries, including the stringency of their climate policies. Second, we use Hassan et al. (2019) Economic Policy Uncertainty (EPU) index to control for the political scenario around environmental issues in each country. This allows us to disentangle the attention factor and its importance for banks' decision to extend financing.

Table 3 shows the summary statistics of the variables within the dataset used for estimation, based on our tranche-level data. The total sample size is approximately 67,000. The logarithm of the allocated loan value to each lender has a median of 16.7, with the 25th and 75th percentiles at 15.6 and 17.6, respectively, which suggests a distribution that is slightly skewed towards the

Table 2: Descriptive Statistics. Climate Policy Index.

	Mean	Std. Dev.	Min	25%	50%	75%	Max
AU	100	98.5	0	15.5	77.3	154.1	441.4
BR	100	96.4	0	26	78.1	146.6	482.9
CA	100	71.8	0	49.4	79.9	148.8	316.8
CL	100	91.6	0	27.3	73.6	149.1	383.9
CN	100	77.6	0	48.9	86.4	135.7	380.4
CO	100	72.4	0	42.6	83.3	146.8	366.8
DE	100	119.4	0	13	62.3	124.4	672.5
ES	100	99.4	0	36.7	85.1	127.1	544.4
FR	100	86.8	0	37.3	74.7	148.8	434.6
IN	100	88.5	0	32.1	68.5	145.1	453.3
IT	100	103.4	0	20.8	68.8	126.6	486.4
JP	100	96.8	0	19.5	77.8	173.5	405.5
KR	100	121.6	0	0	55.3	189.8	437.7
MX	100	81.6	0	42.4	74.4	140.7	445
PT	100	103.3	0	23.6	76	132.9	623.7
UK	100	94.3	0	30.5	80.3	132.4	505.6
US	100	92.8	3.8	34.3	73.2	138.4	516.5

lower end.

Table 4 illustrates the sample distribution categorized by borrower and lender countries. Among borrowers, the United States claims the largest share within our datasets, followed by the United Kingdom and Australia, respectively. Conversely, Japan stands out as the primary lender, contributing a sample size of approximately 12,000 entries, while maintaining a minor presence as a borrower. This trend aligns with the inclination of Japanese firms to seek loans from domestic banks, while Japanese financial institutions demonstrate a greater propensity to extend credit to foreign firms in pursuit of higher yields. Notably, France and other European countries hold a relatively significant share as lenders, driven in part by the active cross-border lending activities prevalent in Europe. Conversely, the United States' share as a lender is relatively modest compared to its position as a borrower.

Table 5 reports the sample size by sector of borrowing firms. The transportation, public utilities, and manufacturing sectors collectively encompass more than half of the observations. The service sector follows as the third largest category. Additionally, the mining sector, categorized as a *brown* sector within our classification, represents 6% of the entire sample.

3 Empirical Model

In our baseline model, we examine whether the climate attention in the lender's home country ($LendCAI_{n_jt-1}$) has an effect on the credit allocation. To do so, we run a panel regression as

Table 3: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
log(allocated tranche value (USD))	69053	16.557	1.586	2.89	23.471	15.581	16.696	17.647
Lender-country CAI	69053	1.111	.761	0	4.691	.543	1.009	1.562
Control variables								
log(Lender-country CCPI)	68987	3.824	.341	2.923	4.26	3.617	3.891	4.083
log(Lender-country EPUI)	68910	5.272	.491	3.296	6.297	4.855	5.24	5.727
Real GDP growth rate (%)	69053	1.182	4.021	-11.3	11.7	.7	1.9	2.8
Exchange rates (log difference)	69029	.001	.024	-.194	.186	-.012	0	.014

Table 4: Sample size by country

Country	by lender country	by borrower country
AUS	1345	7030
AUT	24	0
BRA	107	1225
CAN	11198	4616
CHL	60	704
CHN	2904	578
COL	17	318
DEU	5868	4093
ESP	5473	2785
FRA	10676	3798
GBR	8285	6944
IND	349	793
ITA	2280	2956
JPN	12255	397
KOR	674	277
MEX	1	1816
PRT	119	327
USA	7418	30396
Total	69053	69053

follows,

$$y_{ijkt} = \sum_{b=1}^{3} (beta_b \times IntensityDummy\_b_i) \times LendCAI_{n_j t-1} + \alpha_i + \gamma_j + \eta_{m_i t} + \beta_c Control_{ijt} + u_{ijkt}, \quad (1)$$

where y_{ijkt} indicates the log of the lending amount from lender j to borrower i in deal k at time t. $IntensityDummy\_b_i$ indicates the brownness indicator of firm i. In the baseline case, we use the tertile dummies based on the sectoral average of the GHG emission intens ity. For example, $IntensityDummy\_1_i$ takes one if firm i is categorized in the lowest tertile sectors and zero otherwise. To make it clear, we denote the three tertile group dummies as low, middle, and high intensity dummies. We call sectors in the top tertile group as "brown." For the robustness check, we also use the quintile dummies based on the sectoral average of GHG emission intensity. The list of sectors that are classified in the top tertile or quintile groups is provided in

Table 5: Sample size by sector

Sector	Obs.
Agriculture, Forestry and Fishing	442
Construction	2,076
Manufacturing	19,593
Mining	4,052
Retail Trade	3,572
Services	13,326
Transportation, Communications and Utilities	23,299
Wholesale Trade	2,693
Total	69,053

Table A3 of Appendix.[6] α_i and γ_j denote borrower and lender fixed effects, respectively. $\eta_{m_i t}$ indicates time-varying fixed effects of borrower's country m_i. $Control_{ijt}$ represents a vector of control variables, which includes the CCPI by Germanwatch in lender's country m_i and the growth rate of bilateral exchange rates between borrower i's and lender j's country (*ChgExc*) in month $t-1$. We employ the logarithmic difference of the exchange rate expressed in the lender's country currency to indicate the value of one unit of currency in the borrower's country. To mitigate the endogeneity problem, we use the one month lag of the 3-month average CAI from $t-3$ to $t-1$. As a control variable, we include the lender's home country real GDP growth rate (*LendGDP*) to control for the lender's incentive to seek investment opportunities abroad. As a robustness check, we also use a model satiated with deal-level fixed effects (Benincasa et al. (2022)),

$$y_{ijkt} = \sum_{b=1}^{3} (\beta_b \times IntensityDummy\_b_i) \times LendCAI_{n_j t-1} + \omega_k + \beta_c Control_{ijt} + u_{ijkt}, \quad (2)$$

where ω_k indicates deal fixed effects and it absorbs borrower, lender and time fixed effects. In this specification, we fully control for demand factors and exploit the variation in the CAI in lenders' countries.

4 Estimation results

4.1 Effect of the lender-country CAI on cross-border lending

In this section, we investigate the effect of CAI in a lender's country. More specifically, the impact of the CAI is expected to be more pronounced for loans to firms in brown industries

[6] We use the Standard Industrial Classification (SIC) code for the sector identification.

as the rebalance of portfolio would mainly affect loans to firms with high exposure to climate risks.

4.1.1 Climate policy risk in lender-country

To understand the effect of climate news on cross-border lending, we first focus on the interaction effect between sector GHG intensity dummies and the lender-country CAI. Column (1) of Table 6 presents the estimation results with deal fixed effects as controls. The interaction term between the high-intensity sector dummy and the CAI has a significantly positive coefficient. This result suggests that an increase in the lender-country policy CAI increases the size of cross-border lending to firms in sectors with high GHG intensity. Moreover, the impact is economically significant. A one-standard-deviation increase in the CAI leads to a 1.5 percentage point increase in loan size. The estimated positive interaction effect remains robust even when control variables are included, as shown in Column (2), and when interaction terms for GHG intensity dummies with the lender-country CCPI and EPU are added in Column (3).

As a robustness check, we report estimation results with lender-borrower country fixed effects in Column (4) and with interaction terms between bank variables and GHG intensity dummies in Column (5). Across all specifications, the interaction term between the lender-country CAI and the high-GHG-intensity dummy consistently exhibits a significantly positive coefficient.

To further examine the robustness of our findings, we conduct a regression incorporating interaction terms between the concurrent lender-country CCPI and GHG intensity dummies, as shown in Column (1) of Table 7. The results indicate that the interaction term between the CAI and the high-GHG sector dummy remains significantly positive. This finding suggests that the CAI index captures climate-related policy news that has not yet been implemented. In Column (2), we present the estimation results for the interaction effect between the average sectoral GHG intensity level ($log(SectorInt)$) and the CAI. The estimated coefficient is positive and statistically significant. In Column (3), we augment the equation with time-varying lender fixed effects and dropping the interaction terms for the low and middle intensity dummies to focus on the top tertile dummy. Even with the saturated fixed effects specification, the interaction term between the highest intensity sector dummy and the CAI remains significantly positive.

Finally, in Column (4), we report the estimation results using five sectoral GHG intensity dummies, denoted as $QuinIntDumX$, which take the value of one if the borrowing firm belongs to the Xth quintile group based on average sectoral GHG emission intensity and zero otherwise. The interaction effect is statistically significant only for the highest quintile dummy. This finding

implies that loans to firms within the highest GHG intensity quintile are primarily influenced by an increase in the lender-country CAI.

All estimation results confirm that an increase in the lender-country CAI leads to an increase in the loan size for firms in sectors with the high emission intensity. These results suggest that lenders with an increasing attention to climate policy allocate more credits to foreign firms in brown sectors.

4.2 Exposure to brown sectors and effect of CAI

Banks are often specialized in lending to specific sectors. Previous studies, such as Giannetti et al. (2023), have found that loans to brown sectors tend to be concentrated among particular banks. For policymakers, understanding whether the response to increased climate policy attention varies across banks is of primary importance.

To investigate the heterogeneous effects of banks' past exposure to brown sectors, we include a triple interaction term in the baseline model, specified as follows:

$$y_{ijkt} = \sum_{b=1}^{3} (\beta_b IntensityDummy\_b_i \times BrownExpDummy\_b_{jt}) \times LendCAI_{n_j t-1} + \omega_k + \beta_c Control_{ijt} + u_{ijkt}, \quad (3)$$

where $BrownExpDummy\_b_{jt}$ is an indicator variable capturing bank j's exposure to brown sectors in the past three years in the syndicated loan market. For instance, $BrownExpDummy\_3_{jt}$ equals one if bank j's loan exposure to brown sectors falls in the highest tertile across the sample. More precisely, the three-year syndicated loan exposure ($Brown\_Exposure_{jt}$) is defined as:

$$Brown\_Exposure_{jt} = \sum_{\tau=1}^{3} \frac{Brown\_Sector_{jt-\tau}}{Total\_Loan_{jt-\tau}}, \quad (4)$$

where $Brown_Sector_{jt-\tau}$ represents the total amount of loans provided to firms in brown sectors in year $t-\tau$, and $Total_Loan_{jt-\tau}$ denotes the total amount of syndicated loans in year $t-\tau$.

If lenders with greater exposure to brown sectors are more sensitive to changes in the lender-country CAI, the triple interaction term involving the higher exposure dummy is expected to exhibit a significantly positive coefficient.

The estimation result for the baseline model is presented in the first column of Table 8, indicating that the triple interaction effect with the bank's high-exposure dummy is significantly positive. While the triple interaction term with the middle-exposure dummy is also significantly positive, the coefficient is smaller in magnitude compared to that of the high-exposure dummy.

Table 6: Effect of the lender-country risk adjusted CAI on cross-border lending

	(1)	(2)	(3)	(4)	(5)
LendCAI × LowIntensity	-0.004	-0.003	-0.006	-0.016	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
LendCAI × MiddleIntensity	0.008	0.008	0.009	0.012	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
LendCAI × HighIntensity	0.020**	0.020**	0.021**	0.017*	0.028*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
LendCCPI		-0.011			
		(0.01)			
LendEPU		-0.006			
		(0.01)			
Lender RGDP grwoth		-0.001			
		(0.00)			
ExcRate		-0.213			
		(0.21)			
LendCCPI × LowIntensity			-0.008	0.029	0.017
			(0.02)	(0.03)	(0.09)
LendCCPI × MiddleIntensity			-0.017	0.036	0.072
			(0.02)	(0.03)	(0.10)
LendCCPI × HighIntensity			-0.011	0.034	0.059
			(0.02)	(0.03)	(0.08)
LendEPU × LowIntensity			-0.006	0.007	0.009
			(0.01)	(0.02)	(0.03)
LendEPU × MiddleIntensity			0.022	0.032	0.057
			(0.02)	(0.02)	(0.04)
LendEPU × HighIntensity			-0.019*	0.003	0.039
			(0.01)	(0.02)	(0.04)
Deal FE	Yes	Yes	Yes	Yes	Yes
Interactions with macro variables	No	No	Yes	Yes	Yes
Lender FE	No	No	No	Yes	Yes
Lender × Borrower country FE	No	No	No	Yes	Yes
Interactions with bank variables	No	No	No	No	Yes
Observations	63,390	63,195	63,195	63,101	25,766
Adjusted R-squared	0.670	0.668	0.668	0.669	0.647

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows the estimation results for the panel regression with the loan data at the lender-borrower-tranche level as a dependent variable. *LendCAI* and *LendCCPI* indicate the lender's country CAI and CCPI, respectively. *LendGDP* is the annual growth rate of real GDP of the lender's country in the previous year. *ExcRate* is the monthly growth rates of the bilateral exchange rate between borrower's and lender's countries in the previous month. The standard errors clustered at the lender and monthly-time level.

Table 7: Robustness

	(1)	(2)	(3)	(4)
LendCAI × LowIntensity	-0.015			
	(0.01)			
LendCAI × MiddleIntensity	0.011			
	(0.01)			
LendCAI × HighIntensity	0.017*		0.020*	
	(0.01)		(0.01)	
LendCAI × log(Sector_Int)		0.004*		
		(0.00)		
LendCAI× QuiIntDum1				-0.009
				(0.01)
LendCAI× QuiIntDum2				-0.011
				(0.02)
LendCAI× QuiIntDum3				0.013
				(0.01)
LendCAI× QuiIntDum4				-0.000
				(0.01)
LendCAI× QuiIntDum5				0.021*
				(0.01)
Observations	63,089	63,101	61,604	63,101
Adjusted R-squared	0.669	0.669	0.650	0.669
Deal FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Double interactions (Macro ×Intensity_Var.)	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	—	Yes
Time varying lender FE	No	No	Yes	No
Lender × Borrower country FE	Yes	Yes	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows the estimation results for the panel regression with the loan data at the lender-borrower-tranche level as a dependent variable. *LendCAI* indicates the lender's country CAI. The macroeconomic control variables include the annual growth rate of real GDP of the lender's country in the previous year, the monthly growth rates of the bilateral exchange rate between borrower's and lender's countries in the previous month, the lender-country CCPI, and EPU. The standard errors clustered at the lender and monthly-time level. The standard errors clustered at the lender and monthly-time level.

In the second column, the triple interaction effect remains significantly positive even when including the triple interaction terms of the macroeconomic control variables. To test the robustness of these results, we replace the exposure dummy variable with the level of exposure to brown sectors. The estimation results, shown in the third column, indicate that the triple interaction term with the high GHG emission intensity dummy is significantly positive. This finding suggests that lenders with high exposure to brown sectors are more likely to increase loans to firms in brown sectors when the lender-country CAI increases.

4.3 Heterogeneous impact of climate policy news

4.4 Domestic and Cross-country loans

In the previous estimations, we focused on cross-border lending. However, an increase in climate policy attention within the domestic country could also influence loans to domestic firms. To examine the effect of the CAI on loans, including domestic ones, we estimate the following regression for all loans:

$$y_{ijkt} = \sum_{b=1}^{3} \{(\beta_{b,d} Domestic_{ij} + \beta_{b,c} CrossBorder_{ij}) \times IntensityDummy\_b_i\} \times LendCAI_{n_j t-1} + \omega_k + \beta_c Control_{ijt} + u_{ijkt} \quad (5)$$

where $IntensityDummy\_b_i$ represents the brownness indicator for firm i. In the baseline case, we use tertile dummies based on the sectoral average of GHG emission intensity. For instance, $IntensityDummy\_1_i$ equals one if firm i belongs to the lowest tertile of sectors by GHG emission intensity and zero otherwise. *Domestic* and *CrossBorder* denote indicator variables for domestic and cross-border loans, respectively.

It is important to note that in the previous sections, when analyzing only the sample of cross-border loans, we find $\beta_{3,c}$ to be significantly negative. This result suggests that a higher CAI in the lender's country leads to an increase in cross-border loans to borrowers in brown sectors.

One of the key coefficients of interest is $\beta_{3,dom}$, which captures the response of loans to domestic borrowers in high GHG emission sectors when the CAI increases in the lender country. If lenders are reallocating their lending portfolios from the domestic market to foreign markets to mitigate the increasing climate policy risk in their home countries, this coefficient would be expected to be negative.

The estimation results are presented in Table 10. The first and second columns show the

Table 8: Exposure in the brown sectors and effect of lender-country CAI

	(1)	(2)	(3)
LowIntensity × LowBrownExp × LendCAI	-0.014	0.003	
	(0.01)	(0.01)	
LowIntensity × MiddleBrownExp × LendCAI	-0.012	-0.026**	
	(0.01)	(0.01)	
LowIntensity × HighBrownExp × LendCAI	0.020	0.014	
	(0.03)	(0.05)	
MiddleIntensity × LowBrownExp × LendCAI	0.007	0.017	
	(0.01)	(0.01)	
MiddleIntensity × MiddleBrownExp × LendCAI	0.012	0.009	
	(0.01)	(0.01)	
MiddleIntensity × HighBrownExp × LendCAI	-0.003	0.019	
	(0.03)	(0.06)	
HighIntensity × LowBrownExp × LendCAI	-0.002	0.004	
	(0.01)	(0.02)	
HighIntensity × MiddleBrownExp × LendCAI	0.021**	0.019*	
	(0.01)	(0.01)	
HighIntensity × HighBrownExp × LendCAI	0.034*	0.050*	
	(0.02)	(0.03)	
LowIntensity × LendCAI			-0.046**
			(0.02)
MiddleIntensity × LendCAI			0.033
			(0.03)
HighIntensity × LendCAI			-0.023
			(0.02)
LowIntensity × LendCAI × BrownExp			0.026
			(0.02)
MiddleIntensity × LendCAI × BrownExp			-0.018
			(0.02)
HighIntensity × LendCAI × BrownExp			0.031*
			(0.02)
Observations	61,725	61,725	61,725
Adjusted R-squared	0.669	0.669	0.669
Deal FE	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes
Triple interactions (Macro ×IntensityDummy ×BrownExp)	No	Yes	No
Lender FE	Yes	Yes	Yes
Lender × Borrower country FE	Yes	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows the estimation results for the panel regression with the loan data at the lender-borrower-tranche level as a dependent variable. *LendCAI* indicates the lender's country CAI. The macroeconomic control variables include the annual growth rate of real GDP of the lender's country in the previous year, the monthly growth rates of the bilateral exchange rate between borrower's and lender's countries in the previous month, the lender-country CCPI, and EPU. The standard errors clustered at the lender and monthly-time level.

Table 9: Credit ratings and new relationships

	(1)	(2)	(3)	(4)
	Borrower rating		New relationship	
LowIntensity × HighRating × LendCAI	0.000	-0.001		
	(0.02)	(0.02)		
LowIntensity × LowRating × LendCAI	-0.017	-0.020		
	(0.02)	(0.02)		
MiddleIntensity × HighRating × LendCAI	0.045*	0.050**		
	(0.02)	(0.02)		
MiddleIntensity × LowRating × LendCAI	-0.016	-0.009		
	(0.02)	(0.02)		
HighIntensity × HighRating × LendCAI	0.025*	0.026*		
	(0.01)	(0.01)		
HighIntensity × LowRating × LendCAI	-0.035*	-0.035*		
	(0.02)	(0.02)		
LowIntensity × Ex._Relation × LendCAI			-0.013	-0.020
			(0.01)	(0.01)
LowIntensity × New_Relation × LendCAI			-0.012	-0.008
			(0.01)	(0.02)
MiddleIntensity × Ex._Relation × LendCAI			0.003	0.001
			(0.01)	(0.01)
MiddleIntensity × New_Relation× LendCAI			0.021	0.029*
			(0.01)	(0.02)
HighIntensity × Ex._Relation × LendCAI			0.007	0.005
			(0.01)	(0.01)
HighIntensity × New_Relation × LendCAI			0.029**	0.037**
			(0.01)	(0.02)
Observations	26,215	26,215	63,101	63,101
Adjusted R-squared	0.730	0.730	0.669	0.669
Deal FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Double interactions (Macro ×Intensity_Var.)	No	Yes	No	Yes
Lender FE	Yes	Yes	Yes	Yes
Lender × Borrower country FE	Yes	Yes	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows the estimation results for the panel regression with the loan data at the lender-borrower-tranche level as a dependent variable. *LendCAI* indicates the lender's country CAI. The macroeconomic control variables include the annual growth rate of real GDP of the lender's country in the previous year, the monthly growth rates of the bilateral exchange rate between borrower's and lender's countries in the previous month, the lender-country CCPI, and EPU. The standard errors clustered at the lender and monthly-time level.

results without and with the triple interaction effects of macroeconomic control variables, such as $Intensity \times CCPI \times Domestic$, respectively. Both regressions include lender-country macroeconomic variables. All specifications incorporate deal fixed effects to control for unobserved demand effects from borrowers.

In line with the baseline results using only cross-border loans, the triple interaction term $HighIntensity \times CAI \times CrossBorder$ has a significantly positive coefficient. Additionally, the triple interaction effect for the middle level of GHG emission intensity is also significantly positive.

In the first column of Table 10, the triple interaction effect of CAI with the low-intensity sector and domestic dummies is significantly negative. This finding suggests that lenders in countries with a high CAI tend to reduce loans to domestic firms in sectors with low GHG emission intensity. One possible explanation is that, anticipating an increase in climate policy risk in their own country, lenders expect limited growth in loan demand from borrowers in green sectors, as credit supply has already expanded for these less risky firms. As a result, lenders decrease loans to low-risk borrowers with limited risk premiums while reallocating credit to foreign firms.

The estimation results incorporating all interaction terms of macroeconomic variables, CAI, and the cross-border loan dummy are reported in the second column of Table 10. The coefficient of primary interest, $HighIntensity \times CAI \times CrossBorder$, remains significantly positive. The interaction effect of the low-intensity dummy, CAI, and the domestic loan dummy is negative but not statistically significant.

To test the robustness of these findings, we use quintile dummies based on the GHG emission intensity of the borrowing firms' sectors. The triple interaction term involving the CAI, the highest quintile dummy, and the cross-border loan dummy is significantly positive. Furthermore, the interaction term involving the domestic loan dummy, the lowest quintile dummy, and the CAI is negative, though not statistically significant.

In summary, an increase in the lender-country CAI leads to an increase in the size of cross-border loans to firms in brown sectors, while it reduces the size of loans to domestic firms in sectors with low GHG emission intensity.

5 Conclusions

Our study sheds light on the intricate dynamics between climate policy risk and the allocation of cross-border loans. We introduce three novel Climate attention indexes for a wide set of countries, providing a comprehensive measure that incorporates both policy and public attention to climate issues. Our analysis reveals that higher climate news attention in the

Table 10: Effect of the climate attention index on domestic and cross-border loans

	(1)	(2)	(3)
LowIntensity × Domestic × LendCAI	-0.018**	-0.015	
	(0.01)	(0.01)	
LowIntensity × CrossBorder × LendCAI	0.005	0.000	
	(0.01)	(0.01)	
MiddleIntensity × Domestic × LendCAI	0.007	0.008	
	(0.01)	(0.01)	
MiddleIntensity × CrossBorder × LendCAI	0.017*	0.019*	
	(0.01)	(0.01)	
HighIntensty × Domestic × LendCAI	0.003	-0.006	
	(0.01)	(0.01)	
HighIntensty × CrossBorder × LendCAI	0.016**	0.020**	
	(0.01)	(0.01)	
IntensityQuintile1 × Domestic × LendCAI			-0.017
			(0.01)
IntensityQuintile1 × CrossBorder × LendCAI			0.015
			(0.01)
IntensityQuintile2 × Domestic × LendCAI			-0.004
			(0.01)
IntensityQuintile2 × CrossBorder × LendCAI			-0.000
			(0.01)
IntensityQuintile3 × Domestic × LendCAI			0.008
			(0.02)
IntensityQuintile3 × CrossBorder × LendCAI			0.015
			(0.01)
IntensityQuintile4 × Domestic × LendCAI			-0.014
			(0.01)
IntensityQuintile4 × CrossBorder × LendCAI			0.006
			(0.01)
IntensityQuintile5 × Domestic × LendCAI			0.011
			(0.01)
IntensityQuintile5 × CrossBorder × LendCAI			0.022**
			(0.01)
Observations	222,388	222,388	222,388
Adjusted R-squared	0.742	0.742	0.742
Deal FE	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes
Triple interactions (Macro ×Intensity_Var. ×CrossBorder)	No	Yes	No
Lender FE	Yes	Yes	Yes
Lender × Borrower country FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

borrower's country is associated with a decrease in cross-border loans from foreign banks, indicating a sensitivity to climate risks.

Our contribution extends to the nuanced role of climate attention in the lender's country. We find that lenders not only consider current climate policies but also factor in climate risks, including the potential for future stringent policies, when allocating resources among borrower countries. The Climate Attention Index in the lender's country influences lending decisions, particularly in the case of brown firms, suggesting a strategic response to climate-related risks.

Comparing our approach to existing literature, we distinguish ourselves by focusing on climate attention, encompassing both policy and public awareness, rather than relying solely on policy stringency indices. By examining the influence of climate attention on cross-border lending, we provide empirical evidence of the importance of considering not only formal climate policies but also the broader social and media discourse surrounding climate issues in shaping financial decisions.

References

Altavilla, C., Boucinha, M., Pagano, M., and Polo, A. (2024). Climate risk, bank lending and monetary policy.

Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2023). Climate Change Concerns and the Performance of Green vs. Brown Stocks. *Management Science*, 69(12):7607–7632.

Arteaga, M. J., Colacito, R., Croce, M., and Yang, B. (2023). International Climate News. *Working Paper*.

Baker, S., Bloom, N., and Davis, S. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4).

Benincasa, E., Kabas, G., and Ongena, S. (2022). There is no planet b. *There are Countries B to Z": Domestic Climate Policy and Cross-Border Lending (March 23, 2022). Swiss Finance Institute Research Paper*, (22-28).

Berg, T., Saunders, A., and Steffen, S. (2016). The total cost of corporate borrowing in the loan market: don't ignore the fees. *The Journal of Finance*, 71(3).

Blickle, K., Fleckenstein, Q., Hillenbrand, S., and Saunders, A. (2022). The Myth of the Lead Arranger's Share. *Federal Reserve Bank of New York Staff Reports*, 922.

Chakraborty, I., Goldstein, I., and MacKinlay, A. (2018). Housing price booms and crowding-out effects in bank lending. *The Review of Financial Studies*, 31:2806–2853.

Degryse, H., Goncharenko, R., Theunisz, C., and Vadasz, T. (2023). When green meets green. *The Journal of Corporate Finance*, 78.

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

Fatica, S., Panzica, R., and Rancan, M. (2021). The pricing of green bonds: Are financial institutions special? *Journal of Financial Stability*, 54.

Giannetti, M., Jasova, M., Loumioti, M., and Mendicino, C. (2023). "glossy green" banks: the disconnect between environmental disclosures and lending activities. *Banks: The Disconnect between Environmental Disclosures and Lending Activities (December, 2023). ECB Working Paper*, (2023/2882).

Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-Level Political Risk: Measurement and Effects. *Quarterly Journal of Economics*, 134(4):2135–2202.

Ho, K. and Wong, A. (2023). Effect of climate-related risk on the costs of bank loans: Evidence from syndicated loan markets in emerging economies. *Emerging Markets Review*, 55.

Ivashina, V. and Scharfstein, D. (2010). Loan syndication and credit cycles. *American Economic Review*, 100(2):57–61.

Kacperczyk, M. and Peydró, J. (2022). Carbon Emissions and the Bank-Lending Channel. *Working Paper*.

Meisenzahl, R. (2023). How climate change shapes bank lending: Evidence from portfolio reallocation.

Mueller, I. and Sfrappini, E. (2022). Climate change-related regulatory risks and bank lending.

Sastry, P., Verner, E., and Marqués Ibáñez, D. (2024). Business as usual: bank climate commitments, lending, and engagement. (2921).

Table A1: Description of variables and sources.

Variable name	Description	Source
Loan-level variables		
Lead bank(s)	Based on Dealogic's guidelines it is the bookrunner of the tranche or the mandated arranger, if there is no bookrunner. If there is no bookrunner in the database, we opt for the arranger, documentation agent, facility agent or syndication agent (in that order Chakraborty et al. (2018)).	Dealogic
Loan type	Based on Berg et al. (2016) and Degryse et al. (2023), we classify loans in three major groups: (i) credit lines (incl. revolving and credit facilities), (ii) term loans (incl. term loan A to H) and (iii) other loan types. We use type of the head (first) tranche of the deal.	Dealogic
Num Leads	Number of Lead Banks in the syndicate	Dealogic
All-in pricing	Pricing of loan tranche including Margin and Fees (in bps).	
Maturity	Months between maturity date and settlement date.	Dealogic
Secured	Dummy =1 if the tranche is secured on any assets.	Dealogic
Deal nationality	Nationality where the majority of the borrower's business takes place	Dealogic
Investment Grade	Dummy =1 if deal is registered as investment grade.	Dealogic
Borrower-level variables		
Debt-to-Equity	Total Liabilities over Total Equity	ORBIS
Public Sector	Dummy =1 if borrower's is classified as public sector entity (i.e, SIC between 9100 and 9800)	Dealogic
Size	Total Assets (in log)	ORBIS
Industry	Firms' SIC code (first two-digits)	Dealogic
Rating	Company effective rating (not available for every company).	Dealogic
Nationality	Country where the borrower is incorporated	
Lender-level variables		
Capitalization		ORBIS
ROA		ORBIS
Size	Total Assets (in log)	ORBIS
Relationship-level variables		
Same nationality	Dummy =1 if lead bank and firm have the same nationality (Benincasa et al. (2022))	Dealogic

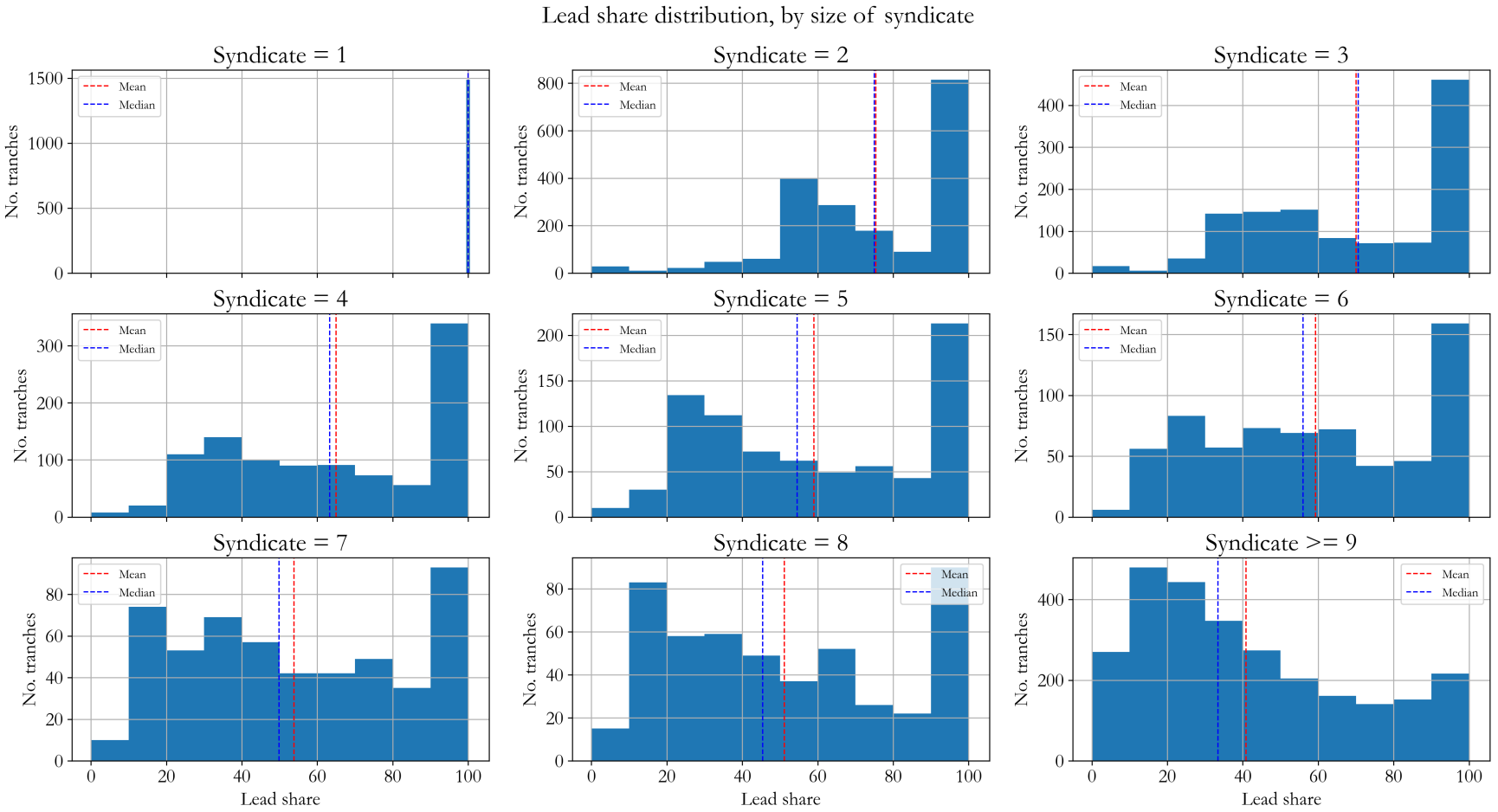

Figure A1: Distribution of lead share, by size of syndicate.

Table A2: Summary of newspapers used in the construction of Climate Attention Index (CAI).

Country	# Outlets	Outlet Name	# of Twitter posts
AUS	4	theage	97,627
		dailytelegraph	109,286
		australian	158,067
		FinancialReview	174,812
BRA	3	folha	433,377
		JornalOGlobo	337,103
		Estadao	320,693
CAN	5	OttawaCitizen	210,555
		TorontoStar	206,038
		VancouverSun	169,969
		globeandmail	319,235
		mtlgazette	165,563
CHL	3	latercera	756,222
		ElMercurio_cl	129,196
		elmostrador	203,037
CHN	3	ChinaDaily	164,618
		PDChina	101,911
		XHNews	221,547
COL	3	elespectador	797,728
		elcolombiano	169,930
		elheraldoco	324,115
DEU	4	zeitonline	174,329
		BILD	245,578
		faznet	174,825
		handelsblatt	113,960
ESP	4	LaVanguardia	443,782
		abc_es	412,669
		el_pais	374,253
		elmundoes	253,798
FRA	4	libe	181,248
		Le_Figaro	275,261
		lemondefr	216,904
		le_Parisien	331,182
GBR	4	thetimes	130,091
		guardiannews	247,422
		FinancialTimes	246,058
		BBCNews	168,358
IND	4	timesofindia	561,925
		htTweets	642,158
		the_hindu	277,174
		EconomicTimes	428,217
ITA	3	repubblica	674,662
		Corriere	377,840

		sole24ore	215,688
JPN	4	JapanToday	101,010
		AJWasahi	33,597
		japantimes	193,269
		The_Japan_News	25,371
KOR	4	TheKoreaHerald	70,152
		YonhapNews	164,003
		koreatimescokr	38,836
		JoongAngDaily	29,955
MEX	4	lajornadaonline	271,643
		El_Universal_Mx	709,930
		Milenio	738,849
		Reforma	321,083
PRT	3	expresso	300,366
		cmjornal	319,040
		JornalNoticias	182,605
USA	11	sfchronicle	197,228
		nytimes	278,242
		latimes	298,373
		dallasnews	207,470
		chicagotribune	187,592
		WSJ	281,073
		USATODAY	209,397
		MiamiHerald	151,816
		BostonGlobe	400,788
		washingtonpost	307,532
		HoustonChron	215,827

Table A3: Brown sectors

Sectors in the top tertile but not in the top quintile
FOOD AND KINDRED PRODUCTS
CHEMICALS & ALLIED PRODUCTS
PETROLEUM REFINING
TIRES & INNER TUBES
RAILROADS, LINE-HAUL OPERATING
TRUCKING & COURIER SERVICES (NO AIR)
TRANSPORTATION SERVICES
WHOLESALE-DURABLE GOODS
SERVICES-AUTOMOTIVE REPAIR, SERVICES & PARKING

Top quintile
METAL MINING
BITUMINOUS COAL & LIGNITE MINING
CRUDE PETROLEUM & NATURAL GAS
MINING & QUARRYING OF NONMETALLIC MINERALS (NO FUELS)
PAPERS & ALLIED PRODUCTS
FLAT GLASS
STEEL WORKS, BLAST FURNACES & ROLLING & FINISHING MILLS
WATER TRANSPORTATION
AIR TRANSPORTATION, SCHEDULED
PIPE LINES (NO NATURAL GAS)
ELECTRIC, GAS & SANITARY SERVICES