Can firms run away from climate-change risk? Evidence from the pricing of bank loans*

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ABSTRACT

We examine how banks perceive and price the effects of climate change on corporate firms. We show that the risk of sea level rise (SLR) increases the spread for long-term loans of affected firms. This effect is stronger when it is harder for firms to relocate or otherwise diversify their SLR risk. Banks also adjust nonprice contractual terms and the loan syndicate structure to manage the risk. Further, we find that banks are subject to limited attention when it comes to this unconventional risk: the spread-risk sensitivity is higher if the lead bank has more experience about the risk and in times of heightened media attention. Finally, affected firms respond to the pricing of the risk by using less long-term debt.

Keywords: Bank loans, Climate change, SLR risk, Collateral, Sea level rise, Syndicated loans

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The discussions leading up to the Paris Agreement underline the ubiquity of climate-change risks across most industries. Yet banks are among the most exposed.[1]

I. Introduction

Climate change is a pressing issue of our time. There is broad consensus in the science community on human-induced climate change and its impact (Wolfson and Schneider (2002)). However, fundamental uncertainties remain, and disagreements and debate continue (Johnston (2010)). The Trump administration, for example, has largely denied the existence of global warming and rolled back regulations and policies intended to mitigate the climate-change risk. Meanwhile, the progressive wing of the Democratic party is championing the ambitious "Green New Deal", which aims for a transition to 100% clean energy by 2020. In the face of these partisan debates, financial markets may play an important role in revealing the cost of climate change via its pricing system. Prices of financial assets distill information from economic agents who bear the financial consequences of their actions (Hayek (1945)). The objectivity and accuracy of market prices suffer less bias since the financial trades are motivated not by bureaucratic requirements but by self-interest (Rajan and Zingales (2003)).

In this paper, we examine whether and to what degree climate change risk affects the cost a firm pays in bank loans. In particular, we examine whether the pricing of bank loans depends on the risk associated with sea level rise (SLR). Banks play an important role in funding corporate America because they allocate large amounts of capital and they specialize in collecting information about and monitoring their borrowers. Thus, banks may be viewed as sophisticated investors who are well positioned to understand and price unconventional factors such as climate-change risk.

Nonetheless, two issues make it uncertain whether banks will price climate change as a financial risk. First, climate change is related to long-run risk. Despite banks' sophis-

[1]Gorodniuk, Anton, 2016, "Beware (and Understand) Corporate Borrowers' Climate-change Risk", www.americanbanker.com

tication, they might nevertheless be unprepared for risk on the long horizon. Indeed, a recent survey by Bank of England suggests that only 10 percent of banks take a long-term view of the financial risk associated with climate change.[2]

Second, whether climate-change risk will translate into a significant financial risk depends on how easily firms can adapt to the change. In theory, firms can reduce or even eliminate SLR risk by relocating to areas free from such concerns. However, relocation can be costly, more so for some firms than others, depending on the firms' geographical diversification, asset types (tangible vs. intangible assets), and the need to be close to networks of workers, customers, suppliers, peer firm competition, and financial markets accessibility. Existing studies show that climate risk affects the pricing of immovable assets associated with real estate, municipalities, and agriculture (Hong, Li, and Xu (2017), Bernstein, Gustafson, and Lewis (2018), and Painter (2018)). It remains unknown how significant a financial risk climate change poses to corporate firms.

Following Hallegatte, Green, Nicholls, and Corfee-Morlot (2013), we measure SLR risk as the expected annual loss relative to the local GDP given a 40 centimeter rise in sea level. We find strong evidence that the spreads for long-term bank loans (i.e., loans with maturity longer than five years) increase with the SLR risk of the county that houses the borrowing firm's headquarters. This relationship is not present for loans with maturity less than or equal to five years, consistent with the notion that SLR is a long-run risk.

We conduct a couple of tests for identification purposes. First, we examine the possibility that higher loan spreads for affected firms are due not to SLR risk, but to some unobserved economic factors that covary with the SLR risk measure. If that is the case, we expect to see higher loan spreads for firms located in counties with similar economic conditions but no SLR risk exposure. We conduct a placebo test based on the premise that neighboring counties have similar economic conditions. Specially, we assign the

[2]Binham and Crow, "Carney plans to test UK banks' resilience to climate change," Financial Times, December 16, 2018, link: https://www.ft.com/content/0ba2390a-ffd4-11e8-ac00-57a2a826423e

SLR risk value of a county exposed to the risk to its adjacent counties with no such risk exposure. We observe no relationship between the loan spread and the hypothetical SLR risk in the placebo test, suggesting that SLR risk is not a proxy for some unobserved economic variables common to neighboring counties. Second, we perform a propensity score matching test. For each firm subject to positive SLR risk, we identify a matching firm with similar characteristics and from the same industry and state, but located in a county with no SLR risk. Our results continue to hold in the matched sample test. We further test our hypothesis on the sample of firm relocation. We find evidence that when a firm relocate its headquarters from a low SLR risk county to a high SLR risk county, its long-term loan cost tends to go up significantly.

If our results are truly driven by differences in SLR risk but not other factors, then we also expect that the effect of SLR risk varies in certain predictable way. In particular, the spread-risk relationship should be stronger when it is harder for firms to relocate or otherwise diversify their SLR risk. We explore the heterogeneity across firms along four dimensions. First, we hypothesize that the spread-risk relationship will be stronger among small firms because they tend to be geographically concentrated and therefore less able to diversify SLR risk. Second, we conjecture that firms with more tangible assets are more sensitive to SLR risk. Tangible assets are most vulnerable to damages caused by the climate risk, and these assets are harder to relocate than intangible assets. Third, we posit that firms with more local customers have fewer incentives to relocate, suggesting the spread-SLR risk relationship will be greater for these firms. Fourth, firms with more local competitors likely have more incentives to relocate, all else being equal, therefore suggesting the spread-SLR risk relationship will be relaxed for these firms. We find supporting evidence for all of these predictions.

We also find that SLR risk affects both nonprice contractual terms and the loan syndicate structure. When the borrowing firm faces SLR risk, banks use more covenants (both financial and general covenants) and increase fees (both upfront and annual fees).

Interestingly, the use of collateral does not increase, suggesting that collateral may not be an effective way to mitigate the specific risk in question (SLR risk can cause severe damage to a firm's collateral assets). The SLR risk also leads to a less concentrated loan syndicate: as the SLR risk increases, the syndicate includes more lenders and the lead bank retains a smaller share of the loan. Overall, the evidence suggests that in addition to charging higher spreads, banks manage risk by adjusting nonprice terms as well as syndicate structure.

Exploring further, we ask whether different banks price SLR risk differently. In a perfect market with full rationality and no information frictions, the identity of the lender should not matter for the pricing of a loan. However, investors have bounded rationality, for example, due to limited attention. We conjecture that banks having more investing experience with affected firms pay more attention to unconventional risk. We divide our sample based on the lead lending bank's past portfolio exposure to SLR risk. We find that the relationship between loan spread and SLR risk is concentrated among loans involving lead banks with high SLR risk experience. Moreover, we report evidence that the spread-SLR risk sensitivity is higher in times of increased media attention to climate change, proxied by spikes in the WSJ climate change news index constructed by Engle, Giglio, Lee, Kelly, and Stroebel (2019), and such impact is short-lived. The evidence thus suggests that even sophisticated investors such as banks are subject to limited attention when it comes to unconventional risks.

Finally, we examine whether firms adjust their debt structure in response to banks' pricing of SLR risk. Given that SLR risk makes long-term loans (but not short-term loans) more expensive, firms may have incentives to use fewer long-term loans and more short-term loans. Consistent with this conjecture, we find that a firm's long-term debt as a percentage of total debt declines with SLR risk.

Our study adds to a growing literature on how financial markets respond to climate-change risk. Based on survey data, Krueger, Sautner, and Starks (2018) report that institutional investors believe climate risks have important financial implications. Ceccarelli, Ramelli, and Wagner (2019) document that mutual fund investors flocked to funds newly rewarded with Low Carbon Designation and that funds respond by adjusting their holdings towards lower carbon risk and by lowering fossil fuel involvement. Baker, Bergstresser, Serafeim, and Wurgler (2018) find evidence that investors pay a premium to green bonds whose proceeds are used for environmentally friendly purposes.

A number of studies examine the prices of immovable assets related to real estate, municipalities, and agriculture. Bernstein et al. (2018) and Baldauf, Garlappi, and Yannelis (2018) document that SLR risk has negative impact on real estate prices, and the effect depends on investor sophistication or belief about climate-change risk. Hong et al. (2017) show that food stock prices underreact to long-term drought risk. Painter (2018) shows that SLR risk increases the spread of long-term municipal bonds. Our paper complements these studies by documenting that the cost of capital for firms is also negatively affected by climate-change risk, suggesting that firms' adjustment costs to climate-change risk are substantial. The effect of SLR risk on the cost of loans is stronger when it is hard for firms to diversify away this risk.

On the asset-pricing side, Bansal, Kiku, and Ochoa (2016) find that equity portfolios with high exposure to climate risk carry a positive risk premium. Engle et al. (2019) use textual analysis to extract innovations from climate change news coverage, and demonstrate that a mimicking portfolio approach can hedge such risk. Giglio, Maggiori, Rao, Stroebel, and Weber (2018) attempt to estimate long-run discount rates for valuing investments in climate-change abatement. Brock and Hansen (2018) highlight the challenges of modeling climate-change risk due to uncertainty.

Our paper also contributes to the banking literature. Consistent with the notion that banks have superior abilities in pricing information, especially soft information (James (1987), Petersen (2019), and Jiang, John, Li, and Qian (2018)), we document evidence that banks understand and price in climate-change risk. We also document that when it comes to unconventional risks such as SLR risk, even banks are subject to attention problems: they pay more attention if they have more experience of the risk, and when the media highlights the risk.

Lastly, our study is the first to document that firms adjust their financial decisions in response to climate-change risk. When the risk affects the cost of long-term debt more than that of short-term debt, firms tend to use less long and more short-term debt.

The remainder of the paper is organized as follows. Section II describes data. Section III presents tests on the effect of SLR risk on firms' cost of bank loans. Section IV examines when banks are more likely to price in SLR risk, and how firms adjust their debt structure to the pricing. Section V concludes.

II. Data

Although climate-change risk can take different forms (e.g. extreme precipitation, extreme drought, and urban heat islands), SLR is one of the most significant risks and the risk most studied by climatologists (Mimura (2013)). Following Hallegatte et al. (2013), we measure the sea level rising risk as the mean annual loss as a percentage of the local GDP based on a 40 centimeter rise in sea level. We assume cities attempt to adapt to the rise in sea level (e.g., by upgrading dikes and sea walls).[3]

Hallegatte et al. (2013) report the SLR risk for major coastal cities across the world. Table I reports the SLR risk of all U.S. cities included in Hallegatte et al. (2013) and their associated counties and states.[4] The city (county) with the highest SLR risk is New Orleans (Orleans Parish), LA, which is expected to have an annual loss of 1.48% GDP due to sea level rise. It is worth noting that even low SLR risk values in percentage terms

[3]Using different magnitudes of sea level rise to capture SLR risk, e.g., 20 cm or 50 cm instead of 40 cm, while resulting in different assessment on the magnitude of the direct damage to the local community, leads to measures that are highly correlated cross-sectionally. As a consequence, such different choices have no discernible effect on all of our results as we focus our analysis on cross-sectional implications.

[4]Hallegatte et al. (2013) report the SLR risk at the city level. In this paper, we measure the SLR risk at the county level by assigning the risk value of a city to its associated county. Results are robust if we measure it at the city level.

can be associated with large dollar losses. For example, although the SLR risk in New York (NY) and Newark (NJ) is only 0.09%, the expected annual dollar losses are over $2.1 billion. It is also worth noting that even though the number of counties that are subject to SLR risk is small (38 out of 552 counties in our loan sample), these counties house the headquarters of so many public firms that about 24% of the loans in our sample are extended to firms subject to the SLR risk.

We extract a sample of bank loans initiated during the 1987–2017 from Thomson Reuters Loan Pricing Corporation DealScan Database. We obtain information including loan pricing, maturity, dollar amount, borrower and lender identities, number of lenders, covenants, and other terms and conditions such as whether the loan has collateral. We measure loan spread by all-in-drawn spread, which is defined by DealScan as the total annual cost, including a set of fees, and fixed spread, paid over London Interbank Offered Rate (LIBOR) for each dollar used under the loan commitment.

We obtain financial data for borrowers from Compustat and their stock price and return data from the Center for Research in Security Prices (CRSP). We exclude financial services (2-digit Standard Industrial Classification (SIC) codes between 60 and 69) and utility firms (2-digit SIC code 49) from the sample. Compustat also provides the location of a firm's headquarters, and we use this information to match county-level SLR risk measure with firm-level variables. After matching, the sample includes 29,697 loans to 4,645 firms with non-missing information for all control variables over the time period 1987–2017.

Panel A of Table II provides descriptive statistics of the full sample of loans. We include in our analysis a host of firm characteristics and deal characteristics that are reported in the literature as relevant for the cost of bank loans. (See Appendix for the full list of variables and their definitions.) The firms in the full sample are located in 552 counties. About 24% (7,019 out of 29,697) of the loans are issued to borrowers headquartered in counties with SLR risk exposure. The average loan spread is about 186 basis points (bps) and the number of lenders in each syndicate is about 8. The summary statistics of the full sample is very similar to other studies using the DealScan database (e.g., Graham, Li, and Qiu (2008) and Engelberg, Gao, and Parsons (2012)).

The effect of SLR risk is likely to be different for long-term versus short-term loans since the climate-change risk concerns mostly uncertain events in the long future. To investigate such difference, we partition the sample into loans with maturities higher than 60 months and those with maturities less than or equal to 60 months (60-month, as a clustering point, is both the median and the 75th percentile for the distribution of loan maturity) and provide descriptive statistics separately in Panels B and C of Table II. Thus, 19% of loans are classified as long-term loans. It is not surprising that the average loan spread is much higher for long-term loans than short-term loans (230 bps vs. 176 bps). Long-term loans are more likely to use collateral and have more lenders and more covenants, all instruments to manage the higher risk associated with the loans. In short, because long-term and short-term loans differ so, we study them separately in our paper.

III. The effect of SLR risk on the cost of bank loans

In this section, we investigate the effect of SLR risk on the cost of bank loans. We present the baseline results in Section III.A and discuss robustness and identification tests in Section III.B. We study the non-pricing terms in Section III.C and discuss the cross-sectional evidence in Section III.D.

A. Baseline results

We examine the effect of SLR risk on the cost of bank loans by estimating the following regression equation:

$$Y_{l,i,j,s,t} = \beta \cdot \text{SLR risk} + \Gamma' X_{l,i,t} + \delta_j + \gamma_s + \eta_t + \epsilon_{i,t} \tag{1}$$

The dependent variable $Y_{l,i,j,s,t}$ is the natural logarithm of the loan spread (all-in-drawn spread) for loan l to firm i (headquartered in state s) in industry j at time t. The main variable of interest is the *SLR risk* at the county level (we also use the natural logarithm of it as an alternative to mitigate the effect of outliers). If banks price in the SLR risk, we expect the coefficient on *SLR risk*, β, to be positive. $X_{l,i,t}$ is a vector of firm and loan characteristics that are reported in the literature as relevant for a firm's loan cost, including *Firm size* (natural logarithm of total assets), *Leverage*, *ROA* (return on assets), *MB* (the market-to-book ratio), *Loss* (a dummy equal to one if the firm has negative net income), *Ret* (stock return in the year before the loan issuance), *Stock return volatility* (daily), *Tangibility* (Property, plant and equipment relative to assets), *Interest coverage*, *ln (Facility amount)*, *ln (Maturity)*, *Collateral dummy*, *Performance pricing dummy*, *Rated dummy* (a dummy equal to one if the firm has a credit rating) and *dummies* for loan type and loan purpose (Graham et al. (2008) and Engelberg et al. (2012)). In the Appendix, we provide definitions of all variables. Following Graham et al. (2008), we also include two macroeconomic variables, *Default spread*, which is the yield spread between BAA and AAA corporate bond indexes, and *Term spread*, which is the yield spread between 10-year Treasury and 3-month Treasury bonds. In all regressions, we include industry (δ_j), state (γ_s), and year (η_t) fixed effects. Standard errors are adjusted for heteroskedasticity and county clustering. Results are robust if we adjust for firm clustering.

We further separate the loan sample into long-term loans (maturity $>$ 5 years) and short-term loans (maturity $\leq$ 5 years). The comparison of the two subsamples allows us to investigate the difference in the lenders' treatment of climate-change risk when they are dealing with long- versus short-term loans. While the science community points to many weather-related events as evidence that climate change's impact on our society is already taking place, the most serious concerns of its impact is in the long-term future. One major uncertainty regarding such long-run impact is the direction and size of feedback effects of the climate system (Johnston (2010)). The most worrying possibility is that the feedback effect can drive Earth's climate to change abruptly. "Even though it is unlikely to occur in the near future, global warming may increase the risk of such events [of abrupt climate changes]."[5] The uncertainty and potential severity of the long-term impact of climate-change risk can greatly influence a risk-averse lender's decision-making around long-term but maybe not short-term loans. For this reason, we expect that SLR risk will have more impact on the costs of long-term loans than of short-term loans.

The regression results are reported in Table III. The results for long-term loans (maturity $>$ 5 years) are in Panel A and those for short-term loans in Panel B. In Column 1 (Column 2) of Panel A, the coefficient on *SLR risk* (ln (*SLR risk*)) is positive and statistically significant, suggesting that firms exposed to higher levels of SLR risk tend to pay higher loan spreads. The impact of SLR risk is also economically meaningful. Estimation from Column 1 indicates that a one-standard-deviation increase in *SLR risk* is associated with a loan spread that is 4.2 basis point higher. The magnitude of the SLR risk effect is comparable to effects documented by recent studies on bank loans. For example, Bharath, Sunder, and Sunder (2008), Hasan, Hoi, Wu, and Zhang (2014), (2017) document that a one-standard-deviation increase in accounting quality, cash effective tax rate, and social capital in their respective samples is associated with a reduction in bank loan spread by 6.7, 4.9, and 4.3 bps, respectively. In Columns 3 and 4 we restrict the sample to 14 states where at least one county is exposed to SLR risk. Our main results continue to hold, i.e., we observe a significantly positive impact of SLR risk on the loan spread, and the economic effect has comparable magnitude as in the whole sample.

In contrast, the results for the short-term loans, reported in Panel B of Table III, are very different. The coefficient on *SLR risk* (or ln (*SLR risk*)) is statistically insignificantly in all specifications, suggesting that SLR risk is not a concern for lenders in their short-term corporate lending.

In summary, the evidence in this subsection shows that firms exposed to high SLR risk pay higher spreads when they borrow long-term loans. The effect of SLR risk on short-term loans is indiscernible. Thus, we focus on long-term loans in the remainder of

[5]The quote on the danger of abrupt climate change is from "Global Warming Impacts," at https://www.ucsusa.org/our-work/global-warming/science-and-impacts/global-warming-impacts.

our analyses.

B. *Identification and Robustness Tests*

We conduct a placebo test to address the concern that the positive relationship between loan spread and SLR risk may be due to their spurious correlations with some unobserved economic factors. Similar to Painter (2018), we identify placebo counties based on geographical proximity. Specifically, for each county subject to SLR risk (a treatment county), we identify placebo counties as counties that are adjacent to and in the same state as the treatment county but are not subject to SLR risk. Thus, the placebo counties are likely to have similar economic conditions as the treatment counties but without SLR risk. We then assign the SLR risk of the treatment county to its placebo counties. If our baseline result is due to spurious correlations between SLR risk and some unobserved economic condition that is common to both the treatment and placebo counties, then these placebo counties will also have higher loan spreads, and we will observe a positive relationship between loan spread and the hypothetical SLR risk for placebo counties. We reestimate Regression 1 for placebo and other counties with no SLR risk but replace placebo counties' SLR risk with the hypothetical value from the treatment county. Table IV reports the results. In the first two columns, placebo counties includes all adjacent counties with zero SLR risk. In the last two columns, for each treatment county we identify just one placebo county that is adjacent and closest in geographic distance to the treatment county. The coefficient on *SLR risk* (or ln(*SLR risk*)) is insignificant across all specifications. The placebo test thus suggests that unobserved local conditions do not drive our main result.

We perform a propensity score matching (PSM) test to further ensure that our results are driven by differences in SLR risk but not other factors. To implement the matching test, we first classify borrowers into treatment and control groups based on whether or not they are subject to SLR risk. The matching begins with a probit regression of the treatment group dummy on the following variables: *Firm size*, *Market-to-book*, *Leverage*, *ROA*, *Loss*, *Stock return*, *Stock return volatility*, *Tangibility*, *Interest coverage*. We require that a matching firm be from the same industry and from an adjacent county in the same state as a treatment firm.[6] We then use the propensity scores from the probit regression estimation and perform a nearest-neighbor match with replacement to other firms. This procedure ensures that a borrower subject to SLR risk is paired with a borrower from the same industry and state and similar in other firm characteristics, but not subject to SLR risk. For 1,171 long-term loans subject to SLR risk, we are able to identify matching loans for 652 of them. The matched sample thus includes includes 1,304 loans. We then reestimate Regression 1 for the matched sample and present the results in Table V. The coefficients of SLR risk and log(*SLR risk*) are 0.288 and 0.481, respectively, and both are statistically significant. The results suggest that the cost of loans increases with SLR risk for firms that are otherwise similar.

To help identify the effect of SLR risk from a firm's headquarters location, we explore the events when firms change headquarters. Such relocation results in potential changes in firms' *SLR* measure, allowing us to compare the same firm's loan spread before and after the SLR change. In this test, the main explanatory variable is *SLR change*, while we include all the control variables seen in Panel A of Table III. Variable *SLR change* equals 1 if a firm move to a county with higher *SLR* (relative to its previous *SLR*) within our sample period, equals 0 if a firm move to a county with the same *SLR*, and equals -1 if a firm move to a county with lower *SLR* (relative to its previous *SLR*). Variable *SLR change* interacts with an indicator variable, *Post*, which equals 1 for the post relocation period. We find a positive significant coefficient for the interacting term. It suggests that when a firm relocate from a county of relatively low *SLR* measure to a county with relatively high *SLR* measure, the firm is likely to see its long-term loan spread increase following

[6] We require a matching firm to be from an adjacent county to maximize the possibility that the two firms experience similar local economic conditions. Relaxing this requirement increases the matched sample to 2,234 (1,117 of treatments have matches). The results are robust.

the relocation.

We conduct a couple of tests to ensure our base-line results are not driven by outliers. We have shown that our results are robust to using the natural logarithm of SLR risk as the independent variable. In addition, we repeat the test by removing the county with the highest SLR risk, Orleans Parish (which contains New Orleans). Our main result is robust to all the alternative specifications.

Finally, we try alternative cutoffs to classify long-term bank loans. In particular, we test whether our results continue to hold when long-term loans are classified as those with a maturity of 6, 7, or 8 years. Our results are robust to all these alternative definitions of long-term loans. The coefficient on SLR risk (or ln(SLR risk)) is positive and statistically significant in all specifications, and the economic magnitude continues to be meaningful.

C. SLR risk effect on other loan contract terms

The banking literature suggests that to manage risk, banks often use nonprice contractual terms as complements to price terms (e.g., Flannery (1986), Berger and Udell (1990), Dennis, Nandy, and Sharpe (2000), Graham et al. (2008). In this section, we explore the effects of SLR risk on nonprice contractual terms and on the loan syndicate structure.

Table VII reports the effects of SLR risk on covenants, fees, loan size, and the use of collateral for long-term loans.[7] We estimate regressions similar to Regression 1 but replace the dependent variable with one of the nonprice terms. For brevity, we only present results for the full sample of long-term loans. Results are robust if we restrict the sample to firms headquartered in the 14 states where at least one county is exposed to SLR risk.

We measure the covenant intensity as the natural logarithm of the total number of

[7]For short-term loans, SLR risk has no effect on any of the nonprice terms. This is consistent with our baseline finding that SLR risk affects long but not short-term loan spread.

covenants. We expect that banks will impose more covenants on firms with higher risk as an alternative way to control risk. Column 1 of Table VII reports the regression result of covenant intensity on SLR risk; the control variables are the same as those in Regression 1. We observe a positive and significant coefficient on *SLR risk*, suggesting that lenders impose more covenants when facing higher SLR risk. In terms of the economic magnitude, for a one-standard-deviation increase in SLR risk, the total number of covenants increases by 2.8%. Following Graham et al. (2008), we also separately measure the number of financial covenants and general covenants. Financial covenants impose limits on certain financial ratios that the borrower has to maintain. General covenants place restrictions on prepayment, dividend payments, term changes, and collateral release. Columns 2-3 of Table VII show that both types of covenants increase with SLR risk.

We next examine whether a firm's SLR risk exposure affects the fees associated with a loan. The borrowing firm pays fees to banks for services such as governing the terms of the loan, administering the drawdown of funds, calculating interest payments, monitoring the firm, and enforcing covenants. The firm pays a one-time fee to lenders at the closing of the deal (the upfront fee), and a recurring annual fee. Fees tend to increase with the complexity and riskiness of the loan. We therefore expect fees to increase with SLR risk. The regression results about fees are presented in Columns (4) and (5) of Table VII. The requirement of fee information largely reduces the sample size. The evidence in Columns (4) and (5) confirms our conjecture: both upfront and annual fees are positively related to SLR risk. A one-standard-deviation increase in SLR risk leads to a 5% increase in upfront fee and a 7% increase in annual fee. The results suggest that banks demand compensation for the increased cost of monitoring firms in the presence of the unconventional SLR risk.

We also examine whether SLR risk affects the use of collateral. Collateral pledging is an important way for a firm to enhance its financial capacity (Barro (1976) and Stiglitz and Weiss (1981)). Riskier borrowers are more likely to use collateral (Berger and Udell (1990)). However, SLR risk in particular can cause severe damages to a firm's collateral assets, such as properties and equipment. Hence the use of collateral may not be an effective way to mitigate this specific risk. Columns (6) of Table VII shows that the use of collateral does not change with SLR risk, consistent with the notion that banks do not view collateral as an effective insurance against SLR risk. Since we restrict our analysis to long-term loans here, we do not examine the impact of SLR on loan maturity. In unreported results, we do find that the likelihood for a firm to issue long-term loans decreases with SLR risk. In section IV.B, we examine how a firm's debt structure (the ratio of long-term debt) depends on SLR risk.

Next, we investigate whether and how SLR risk affects the structure of syndicate loans. There are two possible countervailing effects on the syndicate structure when borrower risk is higher. One the one hand, lenders have higher diversification incentives which will lead to a more diffuse syndicate structure. On the other hand, there can be a greater need for due diligence and monitoring which calls for a more concentrated ownership for the lead bank (Lin, Ma, Malatesta, and Xuan (2012)). Since the SLR risk is largely public information, the first effect is likely to dominate in this context. We therefore hypothesize that higher SLR risk will lead to a less concentrated syndicate structure.

We follow Lin et al. (2012) to construct four measures that capture the concentration of a loan syndicate: the total number of lenders, the loan amount kept by the lead bank, the percentage of the loan kept by the lead bank, and the Herfindahl index of lenders' shares. We regress these four measures on *SLR risk*, and we include other controls from Equation 1. The results are reported in Table VIII. The sample size in Columns 2-4 is largely reduced due to the data requirement on lenders' shares.

The evidence in Table VIII is largely consistent with the notion that higher SLR risk is associated with less-concentrated syndicates for long-term loans. Specifically, when borrowers are subject to SLR risk, the loan syndicate involves more lenders and the lead bank keeps a lower share of the loan. A one-standard-deviation increase in *SLR risk* is associated with a 3% increase in the total number of lenders in a loan syndicate. It is also associated with the lead bank keeping $4.3 million less of the loan. The results thus suggest that banks use the less-concentrated syndicate structure to diversify the SLR risk. Overall, the evidence in this section suggests that in addition to increasing the interest rate, banks also use other loan terms and a more diffuse syndicate structure to manage the SLR risk.

D. Which firms are more vulnerable to SLR risk?

We have shown that firms headquartered in counties with greater SLR risk pay higher interest rates for their long-term bank loans. Thus, firms' cost of capital are affected by the climate-change risk, even though corporate firms has the option to relocate their assets and reduce or eliminate exposure to SLR risk. This is because relocation is costly. Naturally, it will be more costly for some firms than others to relocate or diversify their SLR risk. If our results are truly driven by SLR risk but not other factors, then we should observe that the relationship between SLR risk and loan spread will be stronger for firms that are harder to relocate or diversify SLR risk.

We propose four, non-mutually exclusive factors that may affect firms' abilities to relocate or diversity their SLR risk. First, we expect that small firms are harder to diversify SLR risk because they tend to be geographically concentrated. That is, a greater proportion of their assets and business tend to be located in or around their headquarters. Second, we hypothesize that firms with more tangible assets are more vulnerable to SLR risk. This is because flooding due to sea level rise can cause direct damage to tangible assets such as property, plants and equipment but may not damage intangible assets such as patents, reputation, and goodwill. In addition, it is likely to be more difficult to relocate tangible assets than intangible assets. Third, we conjecture that it is more costly for a firm to relocate if it has more local customers. It makes economic sense to stay close to one's customers because doing so helps to maintain relationships and save shipping costs (Marshall (1920), Ellison, Glaeser, and Kerr (2010)). Fourth, we posit that a firm has greater incentives to relocate if it has more local competitors, all else being equal.

To test these four hypotheses, for each measure of the four factors, we divide firms into two groups, based on the median value of the full sample. We then reestimate Regression 1 for each subsample, and compare the strength of the relationship between loan spread and SLR risk across subsamples.

Table IX focuses on firm size measured as total assets. Columns 1 and 2 show that for small firms (i.e., firms with assets below sample median), the coefficient on *SLR risk* (or *log(SLR risk)*) is positive and significant. In terms of the economic magnitude, based on the estimation in Column 1, a one-standard-deviation increase in *SLR risk* is associated with a loan spread that is 7 basis point higher, which is substantially higher than the economic impact for the full sample. In contrast, Columns 3 and 4 show that for large firms, SLR risk has no significant impact on the loan spread. Thus, the positive relationship between SLR risk and bank loan spread is concentrated among small firms. Large firms, probably because of their geographical diversification, are not as vulnerable to SLR risk.

Table X focuses on firms' asset tangibility, which is measured as the ratio of fixed assets (property, plants and equipment) over assets. Consistent with our conjecture, the effect of SLR risk on loan spreads is concentrated among firms with high tangible assets. A one-standard-deviation increase in *SLR risk* is associated with a 6-basis-point increase in loan spread for this subsample. In contrast, there is essentially no relationship between SLR risk and loan spread for firms with low tangible assets.

In Table XI, we classify the sample based on how many local (potential) customers a firm has. In particular, we estimate the percentage of in-state (potential) customers for each borrower. We use the input-output (IO) tables published by the U.S. Bureau of Economic Analysis (BEA) to identify a firm's major customer industries.[8] We follow Ahern (2012) to require that a customer industry buys at least 1% of a supplier industry's total output to ensure that the industry pair has a meaningful trading relationship. We then identify all public firms in the customer industries as potential customers for a borrower. Using their headquarters information from Compustat, we calculate the percentage of in-state customers. The requirement of customer data greatly reduces sample size.

Table XI shows that the coefficient on *SLR risk* (or *log(SLR risk)*) is statistically significant in both subsamples—firms with a percentage of in-state customers that are greater or less than the sample median. In other words, SLR risk has impact on loan spread for both groups of firms. Nonetheless, the effect is much stronger for the subsample of firms with more in-state customers: the coefficient is about twice as high and the difference is statistically significant. A one-standard-deviation increase in SLR risk increases the loan spread by 5 bps for the subsample of fewer in-state customers (based on Column 1), and increases the loan spread by 11 bps for the subample of more in-state customers (Column 3). Thus, the evidence supports our hypothesis that it is more costly for firms to relocate if they have more local customers and if these firms are more vulnerable to SLR risk. In unreported results, we identify a firm's large customers, i.e., customers that each accounts for at least 10% of a firm's sales from Compustat segment data. The requirement of the existence of such large customers and the availability of their location information further reduces the sample size to 902 observations.[9] But our conclusion holds in the even smaller sample.

Finally, we classify firms based on their percentages of in-state rivals. We identify a firm's rivals as all firms competing in the same product market industry based on

[8]The BEA updates the industry classifications used in the IO tables every five years. Prior to 1997, the IO industries were defined based on the SIC codes. From 1997, the industries are based on the NAICS codes. To maintain consistency over the years in our sample, we use the 2002 IO table in our analysis, which is roughly in the middle of the sample period.

[9]Many of these customers are not public US firms (they can be private firms, governments or government agencies, or foreign firms) and therefore have no information in Compustat.

Hoberg-Phillips industry classification (FIC-100).[10] Results are robust if we classify rivals based on 3-digit SIC code. We then use these firms' headquarters information to calculate the percentage of in-state rivals for each borrower. Table XI reports the results of Regression 1 for the two subsamples based on the percentage of in-state rivals separately. Columns 1 and 2 show that for borrowers with fewer in-state rivals, the coefficient on *SLR risk* (or *log(SLR risk)*) is significantly positive. Based on Column 1, a one-standard-deviation increase in SLR risk increases the loan spread by 5 bps. In contrast, Columns 3 and 4 show that SLR has no significant effect on loan spread for borrowers with more in-state rivals. The results are consistent with the hypothesis that it is less costly for firms to relocate when there are more local rivals.

In summary, the evidence in this section shows that the effect of SLR risk varies in predictable ways across firm types: the effect is stronger if it is more costly for firms to relocate or diversify SLR risk.

IV. Banks' experience and firms' debt structure

A. Banks' SLR risk experience

We have shown, in the previous section, that banks recognize and price SLR risk. This is consistent with them being sophisticated lenders as a group. Nonetheless, every bank may not be equally prepared for this unconventional risk, whose long-run impact is highly uncertain. We thus examine when banks would pay more attention to the SLR risk and are more likely to price the risk. For this purpose. we explore heterogeneity across banks and investigate whether banks' attention to the risk varies with the media attention.

We hypothesize that banks that have more experience with SLR risk are more likely to understand and incorporate the information into the loan price. Therefore, the positive relation between SLR risk and loan spread will be stronger among those transactions

[10] Since FIC-100 is assigned from 1997, this analysis is restricted to the period since 1997.

where the lead bank has more exposure to SLR risk.

To test this hypothesis, we follow Bharath, Dahiya, Saunders, and Srinivasan (2011) to identify lead banks in syndicate loans. We classify a bank as a lead lender if it is a "lead arranger", or if it retains at least a 25% share of the loan and assumes any of the following roles: agent, administrative agent, arranger, or lead bank. In addition, a sole-lender loan by construction has a clearly identified lead bank, which we designate as such. We end up with 4,134 loan facilities with identifiable U.S. lead banks.

We measure a bank's experience with SLR risk as the weighted average SLR risk across its long-term loans. Specifically,

$$\text{A bank's SLR risk experience}_t = \frac{\sum_{j \leq t} \text{loan amount}_j \times \text{SLR risk}_j}{\sum_{j \leq t} \text{loan amount}_j} \tag{2}$$

We then divide the sample into two groups based on the median value of the lead bank's SLR risk experience. We estimate Equation 1 separately for these two subsamples. The results are reported in Table XIII.

Table XIII shows that when the lead bank has high SLR-risk experience (Columns 1 and 2), the coefficient of *SLR risk* (or *log(SLR risk)*) is significantly positive. Estimation from the column 1 indicates that a one-standard-deviation increase in *SLR risk* is associated with a 9-basis-point increase in loan spread. In comparison, the coefficient is insignificant when the the lead bank has low SLR-risk experience (Columns 3 and 4).

The results thus suggest that only banks with adequate experience with SLR risk will price the risk. These banks are on average larger than banks with less SLR experience (average total lending $68 billion vs. $43 billion). But bank size is not what drives the difference. If we divide the sample based on bank size (total lending), we actually find the relationship between loan spread and SLR risk is stronger among small banks, consistent with the notion that small banks pay more attention to soft information or unconventional risk (Stein (2002), Berger, Miller, Petersen, Rajan, and Stein (2005)). Naturally, a large proportion of the high-experience banks are located in coastal states (64%), but many low-experience banks are also located in coastal states—albeit the proportion is lower (41%).[11] Thus, the evidence suggests that it is the experience but not other bank characteristics that lead banks to price SLR risk differently. It takes some learning for even the sophisticated investors to understand and price such an unconventional risk dimension.

Next, we examine whether loan spread sensitivity to SLR risk will increase in times of hightened media attention to climate-change risk. To capture the media attention, we use the *WSJ climate change news index (CCNI)* constructed by Engle et al. (2019). Based on textual analysis, the raw index value describes the fraction of the WSJ dedicated to the topic of climate change. The final index value is the residual from an AR(1) model and therefore is adjusted for the time trend. We obtain the monthly index value from 1987 to 2017. We classify a month as having a media-coverage spike if the index value falls into the top 5% during our sample period. We examine the loan spread in the time period following the media-coverage spike. We include multiple indicator variables: *CCNI spike (1-3)* indicates the first quarter, *CCNI spike (4-6)* the second quarter, and *CCNI spike (7-9)* the third quarter, following the spike month.

To test the moderating effect of media attention on spread-risk sensitivity, we reestimate Equation 1 but add the three time-period indicator variables mentioned above that designate the time periods following a media-coverage spike. Furthermore, we interact *SLR risk* with the time-period indicator variables. We find a significant positive coefficient for the interacting term of *SLR risk* and *CCNI spike (1-3)*, but the coefficients on the interaction of *SLR risk* with *CCNI spike (4-6)* and *CCNI spike (7-9)* are essentially zero. The result suggests that in the quarter following the heightened media attention, the impact of *SLR risk* on a firm's long term loan cost is enlarged. The increase is substantial—Via the comparison of the coefficient on the interacting term *SLR risk* $\times$*CCNI-spike (1-3)* with the coefficient on *SLR risk* itself, the strength of the *SLR risk* effect following the heightened media-coverage spike is two to three times that of a normal period. However, such

[11] The coastal states include New York, California, Texas, Florida, Pennsylvania, Washington, Massachusetts, Rhode Island, Louisiana, and Maryland.

an increase in the *SLR risk* effect due to media attention is short-lived—in the second and third quarter following the media-coverage spike, the strength of the *SLR risk*'s effect goes back to the normal level. Such an interesting pattern of the media-coverage spike's strong initial impact, which then fades quickly and completely, may mirror our limited consciousness that shifts its focus among things competing for our attention. We further note that as Figure 2 of Engle et al. (2019) shows, these spikes tend to occur during influential political and social events such as the Copenhagen UN Climate Change Conference in 2009, the Paris Agreement in 2016, and Trump's withdrawal from the Paris agreement in 2017. They are not usually associated with new scientific discoveries on the topic. These spikes therefore are likely to represent attention changes, rather than new information about the underlying climate-change risks.

Overall, our evidence suggests that when it comes to unconventional risk such as the SLR risk, even sophisticated investors are subject to attention bias: they pay more attention to the risk when they have more experience of it, and when the media highlights the risk.

B. SLR risk and firms' debt structure

The previous section documents that banks charge a risk premium in their long-term loans to corporate borrowers subject to the SLR risk, but not in their short-term loans. In response to this, firms may want to borrow more short-term loans and fewer long-term loans. This can be driven by several reasons. One possible reason is that firm managers are myopic and focus on short-term profits; therefore, they take the risk of higher future borrowing costs (possibly much higher if the climate changes abruptly and the SLR becomes more imminent) in exchange for lower current borrowing costs. Another possibility is that firms differ from banks in their subjective assessment of the climate-change risk, and therefore are not willing to pay the risk premium banks charge for the long-term loans.

To see whether firms subject to SLR risk adjust their debt structure, we estimate the following regression equation:

$$Y_{i,j,s,t} = \beta \cdot \text{SLR risk} + \Gamma' X_{i,t} + \delta_j + \gamma_s + \eta_t + \epsilon_{i,t} \tag{3}$$

The dependent variable $Y_{i,j,s,t}$ here is the ratio of long-term debt (maturity greater than five years) over total debt for firm i (headquartered in state s) in industry j at year t. Both long-term debt and total debt information are from Compustat. This analysis uses 62,461 firm-year observations from 1987 to 2017. This variable has a mean of 0.31 and median of 0.22 in our sample period. The main variable of interest is, as before, a firm's SLR risk. If firms subject to the SLR risk use less long-term debt, we expect to observe a negative (β). We control for various firm characteristics ($X_{i,t}$) that are reported in the literature as relevant for a firm's debt maturity (e.g., Brockman, Martin, and Unlu (2010); Harford, Klasa, and Maxwell (2014)). In all regressions, we include industry (δ_j), state (γ_s), and year (η_t) fixed effects. Standard errors are adjusted for heteroskedasticity and county clustering.

The results are reported in Table XV. The coefficient on *SLR risk* (log(*SLR risk*)) is significantly negative, suggesting that firms subject to higher SLR risk tend to have less long term debt. Estimation from Column 1 indicates that a one-standard-deviation (0.08%) increase in *SLR risk* is associated with a 0.6 percentage-point reduction in the ratio of long-term debt over total debt. Alternatively, a one-percent-point increase in SLR risk leads to a 7.5 percentage-point reduction in the long-term debt over total debt.

We next conduct several tests to ensure robustness. We first repeat the analysis in 14 states with at least one county subject to the SLR risk, and then repeat the analysis by removing firms headquartered in New Orleans (Orleans Parish). In both cases our results remain virtually unchanged. In summary, firms subject to higher SLR risk rely more on short term loans to reduce the current cost of capital.

V. Conclusion

Despite the prevalence of climate-change risk these days, it is unclear how much of a financial risk climate change imposes on corporate firms given that it is a long-term risk and firms might be able to adapt. We shed light on this issue by examining how sophisticated investors such as banks price climate-change risk. We document that the spread of long-term loans (but not short-term loans) increases with one important type of climate-change risk, due to rising sea level. The spread-SLR risk sensitivity is higher when it is harder for the borrowing firm to relocate or otherwise diversify the SLR risk. Moreover, banks use nonprice contractual terms and syndicate structure to manage the risk as well.

Although banks as a group understand and price in unconventional risks such SLR risk, they are still subject to limited attention. The spread-SLR risk sensitivity is higher when the lead bank has more experience about the risk, and when there is heightened media attention to the topic of climate change. Finally, affected firms respond to the pricing effect of SLR risk by using less long and more short-term debt.

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Table I: County-level SLR Risk Measure

This table presents U.S. cities (counties) subject to climate change risk arising from rising sea level, estimated by Hallegatte et al. (2013). The mean annual loss is the optimistic bound calculated assuming a 40 centimeter rise in sea level and assuming that cities attempt to adapt to the rise in sea level. SLR risk is the expected mean annual loss as a percentage of a city's GDP. All counties not included in this table are assigned a SLR risk of zero.

City, State	County	State	FIPS	Mean annual loss	SLR risk
New Orleans, LA	Orleans	LA	22071	1940	1.479%
Miami, FL	Miami Dade	FL	12086	2964	0.420%
Tampa/St. Petersburg, FL	Hillsborough	FL	12057	948	0.324%
Tampa/St. Petersburg, FL	Pinellas	FL	12103	948	0.324%
Virginia Beach, VA	Virginia Beach	VA	51810	328	0.173%
Boston, MA	Suffolk	MA	25025	849	0.149%
Baltimore, MD	Baltimore	MD	24005	299	0.104%
LA/Long Beach/Santa Ana, CA	Los Angeles	CA	6037	217	0.097%
LA/Long Beach/Santa Ana, CA	Orange	CA	6059	217	0.097%
New York, NY/ Newark,NJ	Bronx	NY	36005	2159	0.089%
New York, NY/ Newark,NJ	Kings	NY	36047	2159	0.089%
New York, NY/ Newark,NJ	New York	NY	36061	2159	0.089%
New York, NY/ Newark,NJ	Queens	NY	36081	2159	0.089%
New York, NY/ Newark,NJ	Richmond	NY	36085	2159	0.089%
New York, NY/ Newark,NJ	Essex	NJ	34013	2159	0.089%
New York, NY/ Newark,NJ	Essex	NY	36031	2159	0.089%
Providence, RI	Providence	RI	44007	135	0.083%
Philadelphia, PA	Philadelphia	PA	42101	309	0.044%
Houston, TX	Walker	TX	48471	214	0.038%
Houston, TX	Montgomery	TX	48339	214	0.038%
Houston, TX	Liberty	TX	48291	214	0.038%
Houston, TX	Waller	TX	48473	214	0.038%
Houston, TX	Austin	TX	48015	214	0.038%
Houston, TX	Harris	TX	48201	214	0.038%
Houston, TX	Chambers	TX	48071	214	0.038%
Houston, TX	Colorado	TX	48089	214	0.038%
Houston, TX	Wharton	TX	48481	214	0.038%
Houston, TX	Fort Bend	TX	48157	214	0.038%
Houston, TX	Galveston	TX	48167	214	0.038%
Houston, TX	Brazoria	TX	48039	214	0.038%
Houston, TX	Matagorda	TX	48321	214	0.038%
San Francisco/Oakland, CA	San Francisco	CA	6075	185	0.042%
San Francisco/Oakland, CA	Alameda	CA	6001	185	0.042%
Washington D.C.	Washington	DC	11001	91	0.016%
Seattle, WA	King	WA	53033	90	0.023%
San Diego, CA	San Diego	CA	6073	14	0.004%
Portland, OR	Multnomah	OR	41051	4	0.002%
San Jose, CA	Santa Clara	CA	6085	2	0.001%

Table II: Summary Statistics

Panel A of the table reports the summary statistics of the full syndicate loan sample in our analysis, Panel B reports the long-term (maturity > 60 months) syndicate loan sample, and Panel C reports the short-term (maturity 60 months) syndicate loan sample. The sample of syndicate loans is retrieved from the DealScan database. We exclude financial and utility borrowers from the sample. All variables are defined in Appendix. All the continuous variables are winsorized at the 1st and 99th percentiles. The sample period is 1987–2017.

Panel A: Full sample (1987–2017)						
	N	Mean	P25	Median	P75	Std Dev
SLR risk	29,697	0.020	0	0	0	0.079
Loan spread (basis point)	29,697	185.653	100	175	250	119.783
Loan size ($ M)	29,697	376.434	50	150	400	622.509
Loan maturity	29,697	49.673	36	60	60	23.442
Collateral (dummy)	29,697	0.522	0	1	1	0.500
Performance pricing dummy	29,697	0.444	0	0	1	0.497
Number of lenders	29,684	8.279	2	6	11	8.055
Number of covenants	29,697	4.804	1	4	8	3.837
Total assets	29,697	5,327.190	342.773	1,170.030	4,004.260	12,583.730
Firm size	29,697	7.108	5.837	7.065	8.295	1.751
Market-to-book	29,697	1.676	1.145	1.427	1.907	0.843
Leverage	29,697	0.343	0.196	0.320	0.464	0.210
ROA	29,697	0.026	0.004	0.037	0.068	0.086
Loss (dummy)	29,697	0.227	0	0	0	0.419
Stock return	29,697	0.178	-0.155	0.103	0.391	0.548
Stock return volatility	29,697	0.123	0.080	0.110	0.150	0.060
Interest coverage	29,697	14.567	3.123	6.112	12.985	25.191
Tangibility	29,697	0.318	0.127	0.258	0.464	0.234
Rated (dummy)	29,697	0.510	0	1	1	0.500

Panel B: Long-term bank loan (loan maturity > 60 months)

	N	Mean	P25	Median	P75	Std Dev
SLR risk	5,498	0.021	0	0	0	0.095
Loan spread (basis point)	5,498	229.879	150	225	300	120.644
Loan size ($ M)	5,498	345.511	55	158.55504	400	526.219
Loan maturity	5,498	80.317	72	78	84	17.680
Collateral (dummy)	5,498	0.746	0	1	1	0.435
Performance pricing dummy	5,498	0.364	0	0	1	0.481
Number of lenders	5,493	8.561	2	5	11	8.980
Number of covenants	5,498	5.559	1	5	10	4.523
Total assets	5,498	3,976.120	380.862	1,160.090	3,263.550	9,008.220
Firm size	5,498	7.053	5.942	7.056	8.091	1.595
Market-to-book	5,498	1.604	1.146	1.386	1.794	0.740
Leverage	5,498	0.458	0.297	0.444	0.591	0.231
ROA	5,498	0.017	-0.005	0.025	0.053	0.075
Loss (dummy)	5,498	0.277	0	0	1	0.448
Stock return	5,498	0.206	-0.150	0.122	0.447	0.560
Stock return volatility	5,498	0.124	0.084	0.113	0.150	0.056
Interest coverage	5,498	8.445	2.245	3.889	7.104	17.338
Tangibility	5,498	0.337	0.137	0.291	0.498	0.235
Rated (dummy)	5,498	0.544	0	1	1	0.498

Panel C: Short-term bank loan (loan maturity $\leq$ 60 months)

	N	Mean	P25	Median	P75	Std Dev
SLR risk	24,199	0.020	0	0	0	0.075
Loan spread (basis point)	24,199	175.605	87.5	150	250	117.287
Loan size ($ M)	24,199	383.460	50	150	400	642.179
Loan maturity	24,199	42.711	30	48	60	18.481
Collateral (dummy)	24,199	0.472	0	0	1	0.499
Performance pricing dummy	24,199	0.462	0	0	1	0.499
Number of lenders	24,191	8.215	2	6	11	7.829
Number of covenants	24,199	4.632	1	4	7	3.642
Total assets	24,199	5,634.150	336.561	1,173.720	4,193.320	13,243.320
Firm size	24,199	7.120	5.819	7.068	8.341	1.785
Market-to-book	24,199	1.693	1.144	1.435	1.937	0.864
Leverage	24,199	0.316	0.180	0.297	0.428	0.196
ROA	24,199	0.028	0.007	0.040	0.071	0.088
Loss (dummy)	24,199	0.216	0	0	0	0.411
Stock return	24,199	0.171	-0.156	0.100	0.379	0.545
Stock return volatility	24,199	0.122	0.079	0.109	0.151	0.060
Interest coverage	24,199	15.958	3.474	6.879	14.428	26.459
Tangibility	24,199	0.314	0.125	0.251	0.455	0.234
Rated (dummy)	24,199	0.503	0	1	1	0.500

Table III: The Effect of SLR risk on Long-term and Short-term Loans

The dependent variable in this table is the natural logarithm of the loan spread for syndicate loans. The key explanatory variable is *SLR risk*. Panel A reports results for the long-term syndicate loan sample (maturity > 60 months), and Panel B reports results for the short-term syndicate loan sample (maturity ≤ 60 months). All variables are defined in the Appendix. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Long term loan (maturity > 60 months)

	Log(Loan spread)			
	(1)	(2)	(3)	(4)
	Full sample, 51 states		Subsample, 14 states	
SLR risk	0.192***		0.185***	
	(0.000)		(0.000)	
Log (SLR risk)		0.266***		0.262***
		(0.000)		(0.000)
Firm size	-0.024**	-0.025**	-0.036**	-0.036**
	(0.021)	(0.020)	(0.014)	(0.013)
Market-to-book	-0.072***	-0.072***	-0.089***	-0.089***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.369***	0.369***	0.359***	0.358***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.525***	-0.527***	-0.783***	-0.785***
	(0.002)	(0.002)	(0.000)	(0.000)
Loss	0.039	0.039	0.008	0.007
	(0.145)	(0.148)	(0.839)	(0.846)
Stock return	0.033**	0.033**	0.039*	0.039*
	(0.019)	(0.019)	(0.060)	(0.059)
Stock return volatility	1.588***	1.589***	1.631***	1.634***
	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.134***	-0.133***	-0.121*	-0.120*
	(0.003)	(0.003)	(0.052)	(0.054)
Interest coverage	-0.001	-0.001	-0.001	-0.001
	(0.376)	(0.384)	(0.370)	(0.378)
Log (loan size)	-0.068***	-0.068***	-0.067***	-0.067***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (loan maturity)	-0.013	-0.012	0.006	0.007
	(0.840)	(0.846)	(0.940)	(0.932)
Collateral	0.402***	0.402***	0.383***	0.383***
	(0.000)	(0.000)	(0.000)	(0.000)

Performance pricing dummy	-0.180***	-0.180***	-0.144***	-0.143***
	(0.000)	(0.000)	(0.000)	(0.000)
Rated	-0.016	-0.016	-0.026	-0.025
	(0.369)	(0.377)	(0.217)	(0.224)
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Observations	5,498	5,498	2,916	2,916
R-squared	0.561	0.561	0.563	0.563

Panel B: Short term loan (maturity $\leq$ 60 months)

	Log(Loan spread)			
	(1)	(2)	(3)	(4)
	Full sample, 51 states		Subsample, 14 states	
SLR risk	-0.054		-0.061	
	(0.487)		(0.441)	
Log (climate_risk)		-0.103		-0.112
		(0.337)		(0.296)
Firm size	-0.068***	-0.068***	-0.067***	-0.067***
	(0.000)	(0.000)	(0.000)	(0.000)
Market-to-book	-0.113***	-0.113***	-0.115***	-0.115***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.626***	0.626***	0.609***	0.609***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.280***	-0.281***	-0.283***	-0.283***
	(0.000)	(0.000)	(0.010)	(0.010)
Loss	0.107***	0.107***	0.104***	0.104***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock return	0.053***	0.053***	0.069***	0.069***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock return volatility	1.857***	1.857***	1.698***	1.698***
	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.159***	-0.159***	-0.138***	-0.138***
	(0.000)	(0.000)	(0.005)	(0.005)
Interest coverage	-0.001***	-0.001***	-0.000*	-0.000*
	(0.006)	(0.006)	(0.071)	(0.072)
Log (loan size)	-0.095***	-0.096***	-0.098***	-0.098***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (loan maturity)	-0.074***	-0.074***	-0.066***	-0.066***
	(0.000)	(0.000)	(0.000)	(0.000)
Collateral	0.342***	0.342***	0.321***	0.321***

	(0.000)	(0.000)	(0.000)	(0.000)
Performance pricing dummy	-0.062***	-0.062***	-0.085***	-0.085***
	(0.000)	(0.000)	(0.000)	(0.000)
Rated	-0.016	-0.016	-0.031*	-0.031*
	(0.193)	(0.193)	(0.065)	(0.065)
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Observations	24,199	24,199	13,287	13,287
R-squared	0.665	0.666	0.666	0.667

Table IV: Placebo Test

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variable is *SLR risk*. In Columns 1 and 2, to identify placebo counties, we assign the SLR risk of a county to adjacent counties that are not subject to SLR risk within the same state. In columns 3 and 4, we identify placebo counties based on geographical distance, assigning the SLR risk of a county to the closest non-coastal county (i.e., SLR risk is zero) within the same state. All regressions include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Cost of long-term bank loan, maturity > 60 months

	Log(Loan spread)			
	(1)	(2)	(3)	(4)
SLR risk	0.017		0.119	
	(0.17)		(1.21)	
Log (SLR risk)		0.010		0.136
		(0.08)		(0.75)
Firm controls	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
No. of obs.	4,280	4,280	4,280	4,280
R2	0.569	0.569	0.569	0.569

Table V: Propensity Score Matching Test

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity $>$ 60 months). The key explanatory variable is *SLR risk* in column 1 and *Log(SLR risk)* in column 2. All regressions include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Propensity score matching test

	Log(Loan spread)	
	(1)	(2)
SLR risk	0.288***	
	(0.006)	
Log (SLR risk)		0.481***
		(0.002)
Firm controls	Y	Y
Loan controls	Y	Y
Macro controls	Y	Y
Loan type and purpose FE	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
State FE	Y	Y
Observations	1,304	1,304
R-squared	0.644	0.644

Table VI: Firm Relocation

In this table, we explore the event of a firm relocate its headquarters. Such relocation results in potential changes in firms' *SLR* measure. The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The main new variable is *SLR change*, which equals 1 if a firm move to a county with higher *SLR* (relative to its previous *SLR*) within our sample period, equals 0 if a firm move to a county with the same *SLR*, and equals -1 if a firm move to a county with lower *SLR* (relative to its previous *SLR*). Variable *SLR change* interacts with an indicator variable, *Post*, which equals 1 for the post relocation period. All regressions include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan_spread)	
	(1)	(2)
	Year[-4, 4]	Year[-3, 3] year
SLR change × Post	0.173**	0.135*
	(0.019)	(0.092)
Post	0.027	0.008
	(0.576)	(0.887)
SLR change	-0.032	-0.027
	(0.585)	(0.713)
All controls	Y	Y
All FE	Y	Y
Observations	494	407
R-squared	0.533	0.526

Table VII: SLR Risk Effect on Other Contractual Terms

The dependent variable in this table are: *Log(# of covenants)*, *Log(# of general covenants)*, *Log(# of financial covenants)*, *Log(upfront fee)*, *Log(annual fee)*, and *Collateral*, a dummy equal to one if collateral is used. The key explanatory variable is *SLR risk*. All variables are defined in Appendix. *p*-values based on standard errors, adjusted for heteroscedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1987–2017.

	Log(# of covenants)	Log(# of general covenants)	Log(# of financial covenants)	Log (upfront fee)	Log (annual fee)	Collateral
	(1)	(2)	(3)	(4)	(5)	(6)
SLR risk	0.296***	0.287***	0.097*	0.502**	0.741***	-0.057
	(0.000)	(0.000)	(0.093)	(0.012)	(0.001)	(0.226)
Controls:						
Firm controls	Y	Y	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y	Y	Y
Loan type and purpose FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Observations	5,498	5,498	5,498	1,938	496	5,498
R-squared	0.559	0.483	0.538	0.348	0.366	0.282

Table VIII: SLR Risk Effect on Syndicate Structure

The dependent variables in this table are four measures that capture the concentration of a firms loan syndicate: *total number of lenders*, *amount of loan kept by lead bank*, *percentage of loan kept by lead bank* (%), and *Herfindahl index of lenders shares*, following Lin et al. (2012). The key explanatory variable is *SLR risk*. All regression include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(# of lenders)	Amount of loan kept by lead bank ($MM)	Percentage of loan kept by lead bank (%)	Herfindahl index of lenders' shares
	(1)	(2)	(3)	(4)
SLR risk	0.301***	-45.656**	-11.802*	-0.093
	(0.004)	(0.048)	(0.086)	(0.222)
Firm controls	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
No. of obs.	4,134	1,555	1,555	1,555
R2	0.462	0.284	0.503	0.494

Table IX: The SLR Risk Effect on Small and Large Firms

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variable is *SLR risk*. Columns 1 and 2 report results for small borrowers (total assets below the sample median), and columns 3 and 4 report results for large borrowers (total assets above the sample median). All regression include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan spread)			
	Small borrowers (total assets below median)		Large borrowers (total assets above median)	
	(1)	(2)	(3)	(4)
SLR risk	0.294***		0.140	
	(0.000)		(0.122)	
Log (SLR risk)		0.407***		0.181
		(0.000)		(0.243)
Firm controls	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
No. of obs.	2,748	2,748	2,750	2,750
R2	0.547	0.547	0.608	0.607

Table X: The SLR Risk Effect on Firms with High and Low Tangible Assets

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variable is *SLR risk*. Columns 1 and 2 report results for borrowers with low tangible assets (asset tangibility below the sample median) and columns 3 and 4 report results for borrowers with high tangible assets (asset tangibility above the sample median). All regression include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan spread)			
	Borrowers with low tangible assets		Borrowers with high tangible assets	
	(1)	(2)	(3)	(4)
SLR risk	-0.059		0.270***	
	(0.740)		(0.000)	
Log (SLR risk)		-0.074		0.416***
		(0.724)		(0.000)
Controls:				
Firm controls	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
No. of obs.	2,748	2,748	2,750	2,750
R2	0.550	0.550	0.593	0.593

Table XI: The SLR Risk Effect on Firms with More or Less Local Customers

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variable is *SLR risk*. Columns 1 and 2 report results for firms with percentage of in-state customers below sample median, and columns 3 and 4 report results for firms with percentage of in-sate customers above sample median. All regression include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan_spread)			
	% of in-state customers below median		% of in-state customers above median	
	(1)	(2)	(3)	(4)
SLR risk	0.273**		0.652***	
	(0.024)		(0.001)	
Log (SLR risk)		0.379*		0.715***
		(0.061)		(0.008)
Controls	Y	Y	Y	Y
All FE	Y	Y	Y	Y
Observations	938	938	937	937
R-squared	0.634	0.634	0.660	0.660

Table XII: The SLR Risk Effect on Firms with More or Less Local Competition

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variable is *SLR risk*. Columns 1 and 2 report results for firms with percentage of in-state peers below the sample median, and columns 3 and 4 report results for firms with percentage of in-state peers above the sample median. All regressions include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan_spread)			
	% of in-state peers below median		% of in-state peers above median	
	(1)	(2)	(3)	(4)
SLR risk	0.217***		0.058	
	(0.001)		(0.824)	
Log (SLR risk)		0.302***		0.095
		(0.005)		(0.748)
Controls	Y	Y	Y	Y
All FE	Y	Y	Y	Y
Observations	1,794	1,794	1,815	1,815
R-squared	0.512	0.512	0.509	0.509

Table XIII: Lead Banks with High or Low SLR Risk Experience

The dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variable is *SLR risk*. Panel A reports results for loans with lead banks that are subject to high SLR risk exposure (i.e., lead banks' weighted average SLR risk exposure above sample median) and Panel B report results for loans with lead banks that are subject to low SLR risk exposure (i.e., lead banks' weighted average SLR risk exposure below sample median). All regressions include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan spread)			
	(1)	(2)	(3)	(4)
	High SLR risk exposure		Low SLR risk exposure	
SLR risk	0.408***		-0.045	
	(0.000)		(0.636)	
Log (SLR risk)		0.595***		-0.112
		(0.000)		(0.489)
Firm controls	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y
Loan type and purpose FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
No. of obs.	2,059	2,059	2,075	2,075
R2	0.602	0.602	0.597	0.597

Table XIV: SLR risk Effect in Periods of Heightened Media Attention to Climate Change

In this table, we examine whether loan spread sensitivity to SLR risk changes with media attention to climate-change risk. We use the WSJ climate change news index (CCNI) constructed by Engle et al. (2019). The raw index value describes the fraction of the WSJ dedicated to the topic of climate change. The final index value, at monthly frequency from 1987 to 2017, is the residual from an AR(1) model to adjust for the time trend. We classify a month as having a media-attention spike if the index value falls into the top 5% during our sample period. We construct three indicator variables, *CCNI spike (1-3)* which indicates the first quarter, *CCNI spike (4-6)* the second quarter, and *CCNI spike (7-9)* the third quarter, following the spike month. In the table, the dependent variable in this table is the natural logarithm of the loan spread for long-term syndicate loans (maturity > 60 months). The key explanatory variables are *SLR risk* and Log(*SLR risk*), which are further interacted with the above mentioned three indicator variables. All regression include controls included in the models in Panel A of Table III, but the coefficient estimates are suppressed for brevity. *p*-values based on standard errors, adjusted for heteroskedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Loan_spread)			
	(1)	(2)	(3)	(4)
SLR risk	0.169***	0.177***		
	(0.000)	(0.001)		
Log (SLR risk)			0.237***	0.276***
			(0.002)	(0.001)
SLR risk × CCNI spike (1-3)	0.242**	0.268**		
	(0.037)	(0.043)		
SLR risk × CCNI spike (4-6)		-0.051		
		(0.853)		
SLR risk × CCNI spike (7-9)		-0.066		
		(0.851)		
Log (SLR risk) × CCNI spike (1-3)			0.406*	0.496*
			(0.071)	(0.085)
Log (SLR risk) × CCNI spike (4-6)				-0.204
				(0.548)
Log (SLR risk) × CCNI spike (7-9)				-0.224
				(0.169)
Controls	Y	Y	Y	Y
All FE	Y	Y	Y	Y
Observations	5,498	5,498	5,498	5,498
R-squared	0.561	0.561	0.561	0.561

Table XV: SLR Risk Effect on Firm Debt Structure

The dependent variable in this table is the ratio of a firm's long-term debt (maturity > 60 months) over total debt. We exclude firms without debt in this analysis. The key explanatory variable is *SLR risk*. Panel A reports results for the full sample (maturity > 60 months), and Panel B reports results by excluding firms headquartered in New Orleans (Orleans Parish), LA. All variables are defined in Appendix. *p*-values based on standard errors, adjusted for heteroscedasticity and county clustering, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1987–2017.

Fraction of long-term debt (maturity > 5 years)		
	(1)	(2)
SLR risk	-0.075**	
	(0.036)	
Log (SLR risk)		-0.104**
		(0.016)
Firm controls	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
State FE	Y	Y
No. of obs.	62,461	62,461
R2	0.280	0.280

Appendix. Variable Definitions

Bank Loan Variables	
Loan spread	Measured as all-in spread drawn in the DealScan database. Loan spread is measured in basis points.
Log (Loan spread)	Natural logarithm of the loan spread.
Log (loan maturity)	Natural logarithm of the loan maturity. Maturity is measured in months.
Log (loan size)	Natural logarithm of the loan facility amount. Loan amount is measured in millions of dollars.
Number of lenders	Total number of lenders in a single loan.
Number of covenants	Number of covenants in a loan facility.
Collateral	Dummy variable that equals 1 if the loan facility is secured and 0 otherwise.
Performance pricing dummy	Dummy variable that equals 1 if the loan facility uses performance pricing, and 0 otherwise.
Upfront fee	A fee paid by the borrower upon closing of a loan. Upfront fee is measured in basis points.
Annual fee	The annual charge against the entire loan commitment amount, whether used or unused. Annual fee is measured in basis points.
Loan type dummies	Dummy variable for loan types, including term loan, revolver greater than 1 year, revolver less than 1 year, and 364-day facility.
Loan purpose dummies	Dummy variable for loan purposes, including corporate purposes, debt repayment, working capital, takeover, and so forth.
Firm Variables	
Total assets	Total assets.
Firm size	Natural logarithm of total assets.
Market-to-book	(market value of equity + book value of debt)/ total assets.
Leverage	(Long-term debt + debt in current liabilities)/total assets.
ROA	Net income before extraordinary items/total assets.
Loss	Dummy variable that equals 1 if the net income before extraordinary items is negative in the current and prior fiscal year, and 0 otherwise.
Tangibility	Gross property, plant, and equity/total assets.
Rated	Dummy variable that equals 1 if a firm has an S&P long-term credit rating, and 0 otherwise.

Interest coverage	Operating income before depreciation/interest expense.
Leverage	(Long-term debt + debt in current liabilities)/total assets.
Stock return	Annual stock return
Stock return volatility	Stock return volatility in past 12 months.
Additional Variables	
Credit spread	The difference between the yield of AAA corporate bonds and that of BAA corporate bonds.
Term spread	The difference between yield of ten-year Treasury bonds and that of two-year Treasury bonds.
CCNI spike	We first classify a month as having a media attention spike if the WSJ climate change news index value (residual from an AR (1) model) falls into the top 5% during our sample period (1987–2017). Considering that it takes time to negotiate and issue a loan, we define a loan as priced during a spike period (i.e., CCNI spike=1) if there is a media attention spike in the three months before the loan issuance date.