2-2020

The Impact of Climate Change on the Cost of Bank Loans

Abdullah Al Masum
The University of Texas Rio Grande Valley

Siamak Javadi
The University of Texas Rio Grande Valley

Recommended Citation

Masum, Abdullah Al and Javadi, Siamak, The Impact of Climate Change on the Cost of Bank Loans (February 3, 2020). Available at SSRN: https://ssrn.com/abstract=3717013 or http://dx.doi.org/10.2139/ssrn.3717013

The Impact of Climate Change on the Cost of Bank Loans†

Abdullah Al Masum[*] and Siamak Javadi[**]

February 3, 2020

ABSTRACT

We find that firms in location with higher exposure to climate risk pay significantly higher spreads on their bank loans. This result is robust to different measures of climate risk. Exploiting the economic link between a firm and its customers, we find that the exposure of a firm's customers to climate risk adversely affects that firm's cost of borrowing. In the cross-section, we find that the effect is mainly driven by long-term loans of poorly rated firms that are highly exposed to climate risk. Overall, our evidence suggests a slow increase in lenders' attention to climate risk and that lenders have yet to fully understand and price all dimensions of this risk.

JEL Classification: *G21, G32, Q54*

Keywords: *Climate change, cost of bank loan, loan spread*

† We thank Binay Adhikari, Ahmed Elnahas, Incheol Kim, Mahdi Rastad, Nam Nguyen, Vladimir Atanasov, Bernard Black, Danmo Lin, Mohsen Mollagholamali, Maria Teresa Punzi (discussant) and other seminar participants at the University of Texas Rio Grande Valley, the 2019 Northwestern-Duke Causal Inference, the 2019 Finance of Climate Change at EDHEC Business School in Paris, France for their helpful and insightful comments. All remaining errors are ours.

[*] Robert C. Vackar College of Business and Entrepreneurship, The University of Texas – Rio Grande Valley, Edinburg, TX 78539, USA
Email: abdullahal.masum01@utrgv.edu

[**] Robert C. Vackar College of Business and Entrepreneurship, The University of Texas – Rio Grande Valley, Brownsville, TX 78520, USA
Email: siamak.javadi@utrgv.edu

The Impact of Climate Change on the Cost of Bank Loans

ABSTRACT

We find that firms in location with higher exposure to climate risk pay significantly higher spreads on their bank loans. This result is robust to different measures of climate risk. Exploiting the economic link between a firm and its customers, we find that the exposure of a firm's customers to climate risk adversely affects that firm's cost of borrowing. In the cross-section, we find that the effect is mainly driven by long-term loans of poorly rated firms that are highly exposed to climate risk. Overall, our evidence suggests a slow increase in lenders' attention to climate risk and that lenders have yet to fully understand and price all dimensions of this risk.

JEL Classification: *G21, G32, Q54*

Keywords: *Climate change, cost of bank loan, loan spread*

"Investors are increasingly reckoning with these [climate related] questions and recognizing that climate risk is investment risk. Indeed, climate change is almost invariably the top issue that clients around the world raise with BlackRock . . . They [investors] are seeking to understand both the physical risks associated with climate change as well as the ways that climate policy will impact prices, costs, and demand across the entire economy."

- BlackRock Chairman and CEO Larry Fink's annual letter to CEOs (January 2020)

1. Introduction

In this study, we examine whether and to what extent, climate risk affects firms' cost of capital. Specifically, we investigate whether banks view climate change as a relevant risk factor and incorporate it into different dimensions of their loan contracts. There is mounting evidence on the potential adverse impact of climate risk on the economy and its growth. According to a recent US government report[2], the US economy is likely to lose as high as 10% of its GDP due to climate change by the end of this century. Another study by Economic Intelligence Unit (2015)[3] finds that the Value at Risk (VaR) of manageable assets due to climate risk is $4.2 trillion. More recently, in January 2020, Larry Fink, CEO of BlackRock, one of the world's largest asset managers, announced in his annual letter to CEOs that BlackRock "*will now make climate change central to its investment considerations.*"[4]

Moreover, as Painter (2020) points out climate change has been a top shareholder proposal issue in recent years. Echoing this concern, BlackRock warns in its 2020 letter to CEOs that it will leverage its status as a major shareholder to pressure companies to make adequate progress on

[2] Fourth National Climate Assessment (2018), available at https://nca2018.globalchange.gov. This study predicts that farming in the Midwest would decline by 75% and the southern part could also lose 25% soybean production. Heat stress has been responsible for an average $1.2 billion less dairy production since 2010 and likely to be more extensive in the coming years. Wildfire seasons become the longest and most destructive in the history and the severity is predicted to be six times higher by 2050. Sea levels go up by more than 7 inches over the last century, in lower latitude countries the scenario is even worse.

[3] The Economist Intelligence Unit (2015). *The Cost of Inaction: Recognising the Value at Risk from Climate Change*. [online] London, New York, Hong Kong, Geneva: The Economist Intelligence Unit Limited. Available at: https://www.eiuperspectives.economist.com/sites/default/files/The%20cost%20of%20inaction_0.pdf

[4] NPR News link: https://www.npr.org/2020/01/14/796252481/worlds-largest-asset-manager-puts-climate-at-the-center-of-its-investment-strate.

Link to Annual Letter to CEOs: https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter climate-related issues and will vote against management and board directors who do not. In its 2017 survey, KPMG reveals that "for the first time in the history of its survey, more than 60% of companies across all industry sectors" release a corporate responsibility report[5]. In 2017, 78% of Fortune Global 250 companies released such reports. The continuous and substantial growth of this practice since 2011 (44% in 2011, 55% in 2013, and 65% in 2015) reflects the fact that investors find climate change to be increasingly relevant. The relevance of climate risk becomes even more evident in BlackRock's recent announcement in 2020 that it will require from the firms it invests in to release additional disclosure of climate-related risks and their plans to comply with the guidelines of Paris Climate Accord.[6] Another evidence on the relevance of climate risk to investors is the recent move by Moody's to purchase a controlling stake in Four Twenty Seven, a climate data firm that measures and tracks the impact of climate change on 2,000 companies, 196 countries, and 761 cities and more than 3,000 counties in the US.[7]

Given that climate risk cannot be easily hedged or addressed, how do investors price this risk? Bank loans provide a useful setup to study this question. Parallel to the rise of socially responsible investing, there has been a substantial growth in environmentally sensitive lending as well (Chava, 2014; Cogan, 2008)[8] and the evidence suggests that banks are becoming increasingly sensitive to environmental issues (Chang et al., 2018). Moreover, bank loans have historically been

---

[5] https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2017/10/kpmg-survey-of-corporate-responsibility-reporting-2017.pdf

[6] The 2015 Paris Climate Accord, a multilateral agreement that involves 175 parties (174 states and the European Union), requires a long-term commitment by the signatory parties to reduce their CO_2 emission and their carbon footprints to assure that the increase in global average temperature is kept bellow 2°C.

[7] https://www.nytimes.com/2019/07/24/climate/moodys-ratings-climate-change-data.html

[8] Chava (2014, p. 2223) reports that *"*a large number of banks, representing approximately 80% of the global lending volume, have adopted the Equator Principles (http://www.equator-principles.com), are signatories to the United Nations Environment Programme's Statement by Banks, and have agreed to consider social and environmental issues in project finance.*"* The report by Cogan (2008) also reveals that the global banking sector has a clear agenda to include climate change concerns in their lending decisions and that 72.5% of the banks in the survey are involved in clean and renewable energy lending.

one of the most important sources of external finance (Houston and James, 1996). As a percentage of GDP, bank loans remain an important source of external finance, with lower and upper middle-income economies having a ratio of less than 50% by the end of the 2000s, whereas for high income economies (Organization for Economic Cooperation and Development, (OECD)) this ratio is slightly below 125% (Allen et al., 2013, Figure 1, p. 764). In addition, it is a well-established notion in the banking literature that banks as delegated monitors have access to information that may be unavailable to outsiders, and thus they are in a unique position to assess their borrowers' risk and their ability to repay loans. Therefore, if climate change is a relevant risk factor that affects firms, banks are more likely to take climate risk into account when lending to firms located in areas more vulnerable to climate risk.

Our empirical findings support the view that climate change is a relevant risk factor to lenders and that they charge higher interest rates on loans issued to firms located in states that are more exposed to climate risk. Using Loan Pricing Corporation's (LPC) DealScan database, we show that climate risk is positively and significantly associated with loan spreads for a sample of 40,006 unique bank loans issued to 6,267 unique US firms from 1986 to 2017. For each loan in our sample, we first identify the borrowing firm and then use the state of its headquarter to match it with our measures of climate risk. Our first measure is Palmer Drought Severity Index (PDSI), developed by Palmer (1965). This is a widely used measure in economics, finance and climate research (Dai, 2011; Truel et al., 2017; Hong et al., 2019) that extends back to 1895 and is available for 48 states (excludes Washington D.C., Alaska and Hawaii). We find that a one standard deviation increase in the PDSI Index is associated with 1.6% higher interest on bank loans.

PDSI Index could capture the short-term variation in weather (climate shocks)[9]. Therefore, what we are finding could be simply attributed to the effect of weather rather than that of a long-term trend in climate. In fact, according to National Aeronautics and Space Administration (NASA), *"Climate is how the atmosphere "behaves" over relatively long periods of time."* [10] and climate studies also point out that there is a time trend in temperature rise that leads to varying trends in droughts across different areas over time. To alleviate this concern, we follow Hong et al. (2019) to construct our second measure. Using the long time series of PDSI Index, we estimate a trend-stationary model, an AR (1) model with a time trend, to determine the long-term climate change trend. The coefficient on the time trend is arguably a more reliable measure of exposure to climate risk. We find that a one standard deviation increase in the exposure to this measure of climate risk is also associated with about 1.6% higher interest rate on bank loans, confirming our previous finding. For an average firm in our sample that pays a spread of 1.74% on its loan, a 1.6% increase in spread is equivalent to about a 92% rise in its bank loan cost and tantamount to an additional $10.5 million interest payment. As a robustness check, we use the data from Spatial Hazard Events and Losses Database for the United States (SHELDUS) to construct three more measures of climate risk. These measures are based on the duration (in days) and the losses (in billion dollars) to properties and crops associated with natural hazards linked to climate change. Regression results using these climate risk measures further confirm our earlier findings.

Using a firm headquarter to determine its exposure to climate risk is a legitimate concern with our analysis. Firm headquarter locations are usually close to their operational activities and representative of their core business activities (Coval and Moskowitz, 1999; Pirinsky and Wang,

[9] Moody's defines climate shock as extreme weather events like natural disasters, floods, and droughts and differentiates between climate change and climate shock: https://www.moodys.com/research/Moodys-Climate-change-is-forecast-to-heighten-US-exposure-to--PR_376056
[10] See https://www.nasa.gov/mission_pages/noaa-n/climate/climate_weather.html

2006; Ivkovic and Weisbenner, 2007; Hilary and Hui, 2009; Chaney et al., 2012; Korniotis and Kumar, 2013; Tuzel and Zhang, 2017). Corporate decision makers also reside nearby firm headquarters and they are the key players of the business (Davis and Henderson, 2008). However, a firm's headquarter location and its actual operation location might be different in some cases (Troung et al., 2017), which would undermine the credibility of our findings. We alleviate this concern by exploiting the economic link between a firm and its customers. A firms' customers play a vital role in its growth and economic prosperity. It follows that if a firm's customers are more exposed to climate risk, given the economic link between a firm and its customers, the cost of bank loan for that firm should be higher, if climate change is viewed as a relevant risk factor by lenders. Using COMPUSTAT Capital IQ Segments data, we first identify the location of the customers of the borrowing firms in our sample, and then we repeat our analysis using the long-term climate change trend of the customer locations. Results of this analysis confirm our earlier findings. Specifically, a one standard deviation increase in climate risk exposure of a firm's customers is associated with a 0.78% rise in the interest rate of a loan issued to that firm. Compared to the average loan spread of our sample, this is equivalent to about 45% increase in the cost of bank loans.

Further, climate risk has a long-term and gradual nature and thus, it is more likely to inflict damage in long-term. Therefore, if lenders view climate change as a risk factor, borrowing firms located in states more exposed to climate risk should pay a higher spread on their long-term loans compared to those in states less exposed to climate risk. On the contrary, it is unlikely that lenders price climate risk in short-term loans irrespective of the borrowing firm's exposure to climate risk. Poorly rated firms are also more susceptible to climate risk. The fact that these firms are closer to their default threshold (Merton, 1974) along with their financial constraints, lower borrowing capacity and limited flexibility expose them more to the adverse impact of climate risk. We explore these cross-sectional variations and our results support these predictions.

We find that the adverse effect of climate risk is mainly driven by long-term loans (greater than median maturity) of firms with speculative credit rating that are highly exposed to climate risk (greater than median climate risk). We show that for other loan subsamples that exclude any of these characteristics, the effect becomes statistically insignificant. For example, with a representative specification, we find that a one standard deviation increase in climate risk is associated with a 2.23% rise in the spread of long-term loans issued to poorly rated firms that are highly exposed to climate risk. Whereas, the impact of climate risk on loan spread is statistically insignificant for all other loan subsamples such as short-term loans issued to speculative rated firms that are highly exposed to climate risk.

We further verify our findings by conducting a quasi-natural experiment based on an event that could significantly increase lender's attention to climate risk. Following Painter (2020), we compare the loan spreads before and after the release of the Stern Review in 2006 (Stern, 2008). This is a 700-page report released for the government of United Kingdom and is the largest and most widely known and discussed report related to climate change. Our difference-in-difference analysis around the Stern Review confirms the earlier findings. We find a statistically significant difference of about 7-bps (t-stat = 1.79) in the loan spread between long-term loans of poorly rated firms with high exposure to climate risk and all other loans after the release of the Stern Review. We do not find such result for other loan subsamples.

Furthermore, lenders have other options beyond loan spread to mitigate the risks associated with their borrowers (Dennis et al., 2000; Goss and Roberts, 2011). For example, they can issue secured loans, shorten maturity, and increase up-front fees. We explore these options, and we find weak and suggestive evidence consistent with these predictions when we use the entire sample. However, results significantly improve when we restrict the sample to long-term loans of firms with speculative credit rating that are highly exposed to climate risk. We find that for this loan subsample, as climate risk increases lenders significantly reduce the size of the loan, are more likely to issue a secured loan, and increase the number of covenants while the number of participants of loan syndicate decreases. Specifically, a one standard deviation increase in climate risk is associated with a decrease of 8.64% and 8.14% in the loan size and the number of lenders in the loan syndicate, respectively, and with a 14.3% increase in the number of covenants included in the loan. It also increases the likelihood of issuing a secured loan by about 3%. This set of results is consistent with our earlier findings that the impact of climate risk on bank loans is mainly driven by long-term loans of poorly rated firms that are highly exposed to this risk.

Our paper belongs to a fast-growing literature that investigates the pricing of climate risk in financial markets. Chava (2014) finds that investors demand higher cost of capital for firms excluded by environmental screens (e.g., climate change concerns, substantial emissions etc.), and that lower number of institutional investors and fewer banks participate in their loan syndication. Truong et al. (2017) find that climate change risk in the form of drought is not easily diversifiable and the market prices this risk into firm-level equity risk premium. Similarly, Bernstein et al. (2019) find that sea level rise reduces the value of exposed homes by about 7% compared to unexposed properties. While Hong et al. (2019) find that financial markets underreact to climate risk, Bansal et al. (2016) document that markets do price climate risk. They find a negative impact on asset prices of climate risk. Likewise, Painter (2020) find that the US counties more exposed to climate risk pay greater underwriting fees and initial yields to issue long-term municipal bonds compared to the counties unlikely to be affected by climate change. Our results contribute to this literature and adds to the evidence on the pricing of climate risk. Also, consistent with Painter (2020), our results suggest that investor attention to climate risk is an important factor in pricing this risk.

Our paper also adds to the evidence on the financial consequences of climate risk. These consequences can be in the form of production risk (Hong et al, 2019), reputation, regulatory/litigation risk (Chava, 2014) and physical risk (Painter, 2020). Our results suggest that lenders are concerned about the physical risk of climate change and that they require a premium for bearing this risk. The debate about climate change and its causes have no impact on this premium. Requiring this premium is the consequence of the increased physical risk and uncertainty about repaying loans to lenders caused by climate change, regardless of climate risk realization.

This study also contributes to the literature on the determinants of cost of bank loans. Our results reflect banks sensitivity to climate risk and adds to the evidence on environmentally sensitive lending provided by Chang et al. (2018), Chava (2014), and Cogan (2008). We show that in addition to the usual default risk proxies that affect different aspects of loan contracts (see Dennis et al., 2000), the risk associated with climate change also affects the cost and other features of loans.

This study is organized as follows. Section 2 discusses the data, measurement of climate risk and our empirical design. In Section 3, we report our main empirical findings. Subsample analysis is conducted in Section 4. We examine lenders attention by conducting a quasi-natural experiment around the release of the Stern Report in Section 5. In Section 6, we investigate the impact of climate risk on other features of a loan contract. Section 7 concludes.

2. Data and Empirical Design

2.1. Loan Data

We obtain syndicated loan data from Thomson Reuters Loan Pricing Corporation, DealScan. Specifically, we study loans that originated between 1986 and 2017. DealScan includes data on loan prices, terms, and detailed information related to the lenders and borrowers. Each loan is identified as a distinct observation, and the price and nonprice terms are fixed at the facility level. For each facility, we collect the all-in-spread-drawn variable (the total annual spread, paid over London Interbank Offered Rate (LIBOR)) as a measure for the cost of a bank loan. Firms' accounting information is from COMPUSTAT. Firms with negative all-in-spread-drawn and a leverage ratio more than one are dropped. We merge COMPUSTAT data with the DealScan data using the information available at the end of the most recent year prior to the time of loan origination and the COMPUSTAT-DealScan link provided by Chava and Roberts (2008). An average firm in our sample has financed about 38% of its assets with debt and pays a loan spread of about 174 bps. The average loan facility has a size of about $659 million, matures in about 46 months, and has about 8 participants in the loan syndicate. About 68% of the loans in our sample are secured whereas term loans represent about 27% of the loans in our sample.

[Insert Table 1 about here]

2.2. Measuring Climate Risk

2.2.1. PDSI data

We collect historical PDSI data from National Climate Data Center (NCDC) of US National Oceanic and Atmospheric Administration (NOAA)[11] updated in monthly frequency and extends back to 1895. This data is collected by specific measuring geo-stations from 48 different states

[11] Available at www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers [Accessed on December 15, 2018]

(the dataset is not available for Alaska and we exclude data from Hawaii so our focus would be on the US mainland). Following Truong et al. (2017), we aggregate the data to state level by taking the average of the monthly PDSIs across all geo-stations for each state. We then aggregate this measure to state-year level by taking the average of monthly state PDSIs from June of year $(t - 1)$ to May of year t. PDSI is standardized to a range from -10 to +10 where the lower values indicate more severe droughts. To make the exposition easier, we use the negative of PDSI (NEGPDSI) as the measure of climate risk in our analysis, where higher values are associated with greater climate risk. This climate risk measure has a mean value of -0.061 across all states during our sample period. Standard deviation of this measure is about 1.67, more than twice the mean, suggesting substantial variation in our climate risk measure.

2.2.2. Trend analysis

While our first climate risk measure, NEGPDSI, is fairly accurate in measuring drought intensity and is widely used in climate studies, it can also reflect short-term variation in weather. However, climate change is mainly viewed as a change in long-term trend in climate and climate scientists investigate long-term trends of weather patterns for climate change analysis.[12] Following Hong et al. (2019), we address this issue by exploiting the long time-series data available for PDSI that stretches back to 1895 and estimating a trend-stationary model, an AR (1) model with a time trend. The coefficient on the time trend is arguably a more reliable measure of exposure to climate risk since it captures the long-term trend in climate:

$$\boldsymbol{PDSI_{s,t} = a + b * Time_s + c * PDSI_{s,t-1} + \varepsilon_{s,t}} \qquad \textbf{(1)}$$

[12] See https://www.climate.gov/taxonomy/term/3434

Here, our parameter of interest is the coefficient of Time, b, which captures the differential time trends in droughts of each state as well as the longer-run climate change vulnerability of the states through droughts. We estimate regression (1) month by month for each state from 1986 to 2017. We construct our second measure of climate risk that captures the long-term trend of climate, by taking the average of the monthly time coefficients for each state. To remain consistent with our first measure, we multiply our trend measure by -1. In this way, the greater the trend variable, TREND, the lager the exposure to climate risk. This climate risk measure has a mean of -0.022 and a standard deviation of 0.061 which is almost three times larger than the mean, implying substantial variation in this measure. Moreover, the correlation between TREND and NEGPDSI is about 34% and statistically significant.

Table A.2 in the appendix reports the results of the AR (1) model and provides states ranking in terms of climate change trends. Reported time trend coefficients and the resulting state ranking are based on the average of all the time betas across all months for every state. California has the highest climate change long-term trend with the average time beta value of 0.071 while Vermont has the lowest climate change long-term trend with average time beta value of -0.227. Some of the states with higher long-term climate change trend are Florida, New Jersey, Montana, Connecticut, Delaware, Wyoming, Utah, Arizona, Colorado and Nevada. Accordingly, some of the states with lower climate change trend are New Hampshire, Alabama, Mississippi, Tennessee, Michigan, Louisiana, New York, Kentucky, Indiana and Maine. The other states fall in between, having moderate long-term climate change trends. Figure A.1 (in the Appendix) is a graphical representation of the evolution in the long-term trend change in climate for 48 mainland states of the US. There are clearly substantial differences in trend patterns among states. While some of the states show gradual increasing trends towards drought, few others show the gradual inclination towards the moistures. To better highlight this issue in figure1 below, we depict the trend pattern for California and Vermont.

[Insert Figure 1 about here]

Finally, we merge these climate risk measures with our Dealscan loan data by first determining the headquarter of the borrowing firms in our sample from COMPUSTAT and then merge the datasets based on state and year. The final dataset contains 40,006 unique bank loans issued to 6,267 unique US firms from 1986 to 2017.

2.3. Empirical Design

We formally investigate the impact of climate risk on loan spreads by estimating the following regression model:

$$\boldsymbol{Log\ (Spread)_{i,j,k,t} = \alpha + \beta * Climate\ Risk_{k,t} + \gamma * Firm\ Controls_{j,t} + \delta * Loan\ Controls_{i,t} + Industry_j + Year_t + \varepsilon_{j,k,t}} \qquad \textbf{(2)}$$

Here, the unit of observation is facility (loan), i≡loan ID, j≡firm ID, k≡firm headquarter state ID, and t≡time. The dependent variable, Log (Spread), is log-transformed version of loan spread which is the all-in-drawn spread over LIBOR (i.e., the amount paid by borrowers annually over LIBOR in basis points). The coefficient of interest is β. A positive and statistically significant β would suggest an adverse impact of climate risk on cost of bank loans. Following the literature (e.g., Bradley and Roberts, 2015; Qian and Strahan, 2007; Graham et al., 2008; Chava, 2014), we also include a wide range of control variables that could potentially affect the cost of bank loans. These control variables include borrower and loan characteristics.

The first set of these variables controls for borrower characteristics and includes asset size, profitability (ROA), Market-to-Book and leverage. It is important to control for size because on the one hand, larger firms have less trouble accessing external financing and have fewer information asymmetry problems. Therefore, they are likely to have a lower cost of bank loans. On the other hand, due to their sheer size, larger firms can borrow more and as a result may have higher borrowing costs. We also control for firms' profitability because profitable firms have a lower chance of default and are expected to pay a lower spread on their loans. Leverage is another firm-level control variable. It is one of the main inputs in Merton's (1974) distance to default formula; thus, firms with a higher leverage ratio have a higher default risk. All else equal, these firms are expected to have a higher cost of bank loans, making it imperative to control for leverage.

A second set of control variables is related to loan characteristics. These variables include all loan types and purposes. Loan purposes are generally categorized into capital expenditures, backup line, general purposes, recapitalization, refinancing, acquisitions, and other purposes. We also control whether a loan is a term loan. Detailed information about all variables, their sources, and measurements are provided in Table A.1 in the Appendix.

All regression specifications include year fixed effects and industry fixed effects. Given that some banks may be more sensitive to climate risk, we also include bank (lending) fixed effect. We use DealScan's lenders dataset to identify the main lender. We also use on-way cluster robust standard errors at the firm level as well as two-way cluster at the firm and state level in separate specifications.

3. Empirical Findings

3.1. Univariate Analysis

Our first evidence on the adverse impact of climate risk on the cost of bank loan is reported in Table 2. In panel A, the correlation between loan spread and our two measures of climate risk is positive and statistically significant. In panel B, we sort loan facilities into quartiles based on their exposure to climate risk and report the mean loan spread for the bottom (minimum exposure to climate risk) and the top quartile. Irrespective of the climate risk measure, firms in the top climate risk quartile pay significantly higher spread on their loans, between 21- to 15-basis points, compared to those in bottom quartile.

[Insert Table 2 about here]

It is noteworthy to highlight that belonging to top or bottom quartile of climate risk is exclusively determined by the state where a firm headquarter is located. It is unlikely and hard to argue that climate risk was a significant factor when firms chose a state for their headquarter. Therefore, if we accept the premise that climate risk is relatively exogenous, the significant difference in the loan spreads resulting mainly from the difference in the geographical location of firms' headquarter is a reliable indication that climate risk does have an adverse impact on the cost of bank loan.

3.2. Loan Spread and PDSI

For the first set of regressions, we use the drought index, NEGPDSI, as our first measure of climate risk. Results are reported in Table 3. In all specifications, the coefficients on climate risk are positive and statistically significant. The magnitude of these coefficients does not vary with model specifications, suggesting a robust adverse impact of climate risk on loan spreads. The effect is also economically significant. Taking the average of the climate risk coefficients across all model specification (0.0095), we find that a one standard deviation increase in NEGPDSI (1.675) is associated with about 1.6% increase in the loan spread. For an average firm in our sample that pays an interest rate of 1.74% on its loan, a 1.6% increase in its loan spread is equivalent to a 92% surge in its cost of bank loan and tantamount to an additional $10.5 million in interest payment.

[Insert Table 3 about here]

The coefficients of the control variables in all specifications have the expected sign and consistent with the prior literature (Bradley and Roberts 2015; Chava et al. 2009; Chava, 2014). Larger firms have lower loan spreads, whereas firms with higher leverage have higher loan spreads. More profitable firms pay lower interest on their loan (though the effect is statistically insignificant). Firms with high market to book ratio are relatively farther from financial distress and therefore pay a lower loan spread.

3.3. Loan Spread and Trend

Our findings in the previous section could be attributed to the short-term variation in weather rather than climate change. The reason is that climate change is about the change in the long-term trend in the climate. To address this issue, in this section we use our second measure of climate risk, TREND, defined in Section 2.2.2, in regression model (1). Results are reported in Table 4. We find a robust positive association between TREND and loan spread. Focusing on the last column that has the richest set of fixed effects with two-way clustering of standard errors at the firm and state levels, the coefficient on TREND (β=0.214; t-stat=1.73) indicates that a one standard deviation increase in TREND (0.061) is associated with about 1.3% increase in loan spread. Compared to the average loan spread (1.74%), a 1.3% increase is equivalent to about 75% rise in the cost of bank loan. This result is consistent with our earlier finding in Table 3. In fact, if we take the average of all the TREND coefficients across all specifications, the economic effect is identical to that of the PDSI index reported in Table 3: a one standard deviation increase in the climate risk (TREND) is associated with 1.6% rise in the loan spread.

[Insert Table 4 about here]

3.4. Loan Spread and SCHELDUS: A Robustness check

We further confirm these results by using three more measures of climate risk. We construct these measures from Spatial Hazard Events and Losses Database for the United States

(SHELDUS) [13] maintained by Arizona State University. We use the latest released version (version 17: November 8, 2018). The database contains information about the duration (in days) of different types of natural hazards and losses associated with them (e.g., injuries, fatalities, property and corporate losses in dollar amount etc.). We construct these measures using the (natural log of) duration, the property losses and corporate losses (both in billion dollars adjusted for 2017) associated with natural hazards that are linked to climate change, namely hurricanes, thunderstorms, floods, tornados, and heavy rainfalls.

The correlation between these three measures, NEGPDSI and TREND ranges from -0.059 to 12.8, indicating that these measures possibly capture a different dimension of climate risk. Correlations between these measures and TREND and NEGPDSI are reported in Table A.3. in the Appendix. We estimate regression model (2) using each of these climate risk measures separately. Results are reported in Table 5 and they corroborate our earlier findings. Coefficient on climate risk is positive and statistically significant in all specifications for all three measures.

[Insert Table 5 about here]

3.5. Loan Spread and Customer Climate Risk Exposure

A legitimate concern with our analysis is using a firm headquarter location to determine its exposure to climate risk. Pirinsky and Wang (2006) find that stock returns of firms in the same geographical area have strong comovement. Chaney et al. (2012) argue that a firm's major production plants are usually clustered in the same state where the headquarter is located. Using COMPUSTAT data, Truong et al. (2017) find that firms have greater real estate ownership in headquarter state, suggesting a firm headquarter location is a reasonable proxy for the location of their operation. However, this approach has limitations. It is easy to argue that a firm headquarter,

[13] Accessed from https://cemhs.asu.edu/sheldus

and its main operation locations may not necessarily be the same. This issue could undermine the credibility of our findings. In this section we exploit the economic link between a firm and its customers to alleviate this issue and provide further evidence on the adverse impact of climate risk on the cost of bank loan. We use COMPUSTAT Capital IQ Segments data to identify the location of the customers of the borrowing firms in our sample. COMPUSTAT Customer Segments data provides the geographical area of a firm's customer (basically by country or region).

A borrowing firm in our sample may have foreign customers reported on Customer Segments data. Therefore, we collect global PDSI data from NCAR[14]. Calibrated global PDSI data are available in monthly frequencies from January 1850 to December 2014 and for specific geographic longitude and latitude coordinate points. We convert these points to their physical locations (countries) by reverse geo-coding[15]. Given the superiority of TREND, the long-term trend, in measuring climate risk, we use this measure for the current analysis and the rest of the paper. We determine the long-term time trend following the procedure described in Section 2.2.2. Once again, for the ease of exposition and to remain consistent with previous analyses, we use the negative of the time trend coefficient (the larger value would indicate greater climate risk exposure). In the next step, we first merge this newly constructed country-level climate risk measure with customer segments data using customer country and year and then merge that with our working dataset. The final dataset contains climate risk exposure of the borrowing firms in our sample as well as that of their customers. Employing this dataset, we use the climate risk of the borrowing firms' customers and estimate regression model (2). The economic link between a firm and its customer suggests that if the customers of a firm are more exposed to climate risk, lenders

[14] Accessed from https://www.esrl.noaa.gov/psd/data/gridded/data.pdsi.html [Accessed on June 25, 2019]
[15] We use https://www.latlong.net/Show-Latitude-Longitude.html

should charge a higher interest on the loan issued to that firm, predicting a positive coefficient on customers' climate risk variable in model (2). Results reported in Table 6 support this prediction.

[Insert Table 6 about here]

We document a robust positive association between the climate risk exposure of the customers and the loan spread of the borrowing firms that are both statistically and economically significant. This result is consistent with our earlier findings. The magnitude of the coefficients is insensitive to model specifications, establishing more confidence in identifying the adverse economic impact of climate risk on cost of bank loan. Specifically, our results indicate that a one standard deviation increase (0.05) in the climate risk exposure of our borrowing firms' customers is associated with about 0.78% increase in the cost of loan. For an average firm in our sample that pays a loan spread of 174-basis point, a 0.78% rise is equivalent to about 45% increase in the cost of bank loans and additional $5.1 million interest payment. Given the economic link between our sample firms and their customers and that climate risk is arguably exogeneous, these results establish more confidence in a casual interpretation of our findings.

4. Subsample Analysis

4.1. Loan Portfolio Sorts

Climate risk has a long-term nature in a sense that it is more likely to cause more destruction and loss in a few decades in the future compared to a few years. Therefore, firms seeking loans with longer maturities are more likely to be adversely affected; and borrowing firms located in states more exposed to climate risk should pay a higher spread on their long-term loans compared to those in states less exposed to climate risk. On the contrary, lenders are unlikely to price climate risk in short-term loans.

In our first test, we independently sort loan facilities into quartile groups based on their maturity and their exposure to climate risk. Results in Table 7 show that for each maturity quartile, average loan spread increases with exposure to climate risk and the difference between the top and bottom climate risk quartile for each maturity group is statistically significant. For example, focusing on the top (bottom) maturity quartile, the group with longest (shortest) maturity, the difference in the average loan spread between the top climate risk quartile and the bottom climate risk quartile is about 11-bps (17.5-bps) and statistically significant. Likewise, for each climate risk quartile, loan spread increase with maturity. In the top (bottom) climate risk quartile, the group with the highest (lowest) exposure to climate risk, the difference in the average loan spread between the top maturity quartile and the bottom maturity quartile is about 75-bps (81-bps) and statistically significant. The mean loan spread of a loan portfolio that has the highest exposure to climate risk and longest maturity is greater than that of a loan portfolio with lowest exposure to climate risk and shortest maturity by more than 92-bps and statistically significant.

[Insert Table 7 about here]

4.2. Loan Subsample Regressions

In this section, we investigate the cross-sectional heterogeneity in the effect of climate risk on the cost of bank loan more formally by running regressions for a series of loan subsamples. Our evidence from loan portfolios in the previous section provides compelling evidence that the adverse effect of climate risk is stronger for loans with longer maturities. In addition to loans with longer maturity, the adverse impact of climate risk is also expected to be more pronounced for poorly rated firms. Moody's has viewed climate change as a credit risk factor for states and counties as early as November 2016.[16] This view is stressed in another announcement a year later in November 2017 [17] and further expanded to include corporation by their acquisition of a controlling stake in Four Twenty Seven, a climate data company that assesses the climate risk

[16] https://www.moodys.com/research/Moodys-sets-out-approach-to-assessing-the-credit-impact-of--PR_357629
[17] https://www.moodys.com/research/Moodys-Climate-change-is-forecast-to-heighten-US-exposure-to--PR_376056

exposure of firms in addition to countries, cities and counties. The global head of assessments at Moody's Investors Service says that *"We are taking these risks very seriously"*. As highlighted in Moody's reports and Painter (2020), having higher debt capacity is particularly crucial. Firms with poor credit ratings are not only closer to their default threshold but also suffer from financial constraints and lower borrowing capability which collectively results in limited financial flexibility. This issue impedes their ability to raise funds to cover the losses caused by climate risk or finance projects to prevent and mitigate its impact. Therefore, if lenders recognize this issue, the adverse impact of climate risk should also be more pronounced for poorly rated firms.

[Insert Table 8 about here]

We explore these cross-sectional variations and report the results in Table 8. In Panel A, results confirm that the adverse effect of climate risk is mainly driven by poorly rated firms. We split the sample into investment and non-investment subsamples. Firms with a BBB rating or better are categorized into the investment group, and firms with credit rating below that are in the non-investment group. In all specifications, the coefficients on TREND are positive and statistically significant for the non-investment subsample whereas they are insignificant for the investment subsample.

In Panel B, we split the sample into loans with high and low maturity. If a loan maturity is larger (smaller) than the sample median, it belongs to the long (short) maturity category. Results are inconclusive. We find that the adverse effect of climate risk is relatively more pronounced for long maturity subsample when using specifications with lower number of fixed effects (columns 1 to 3). However, the difference in the size of the TREND coefficient between the two groups decreases substantially as model specifications become stricter (columns 4 to 6). In the last two specifications (columns 4 and 5) that have the richest set of fixed effects and clustering of standard errors the TREND coefficient is statistically insignificant for both categories.

The above result is seemingly inconsistent with our conjecture about the impact of maturity and appears to contradict our earlier findings from sorting loan portfolios reported in Table 7. However, loan portfolios are independently sorted based on their maturity *and* their exposure to climate risk. Therefore, the insignificant result in Panel B of Table 8 combined with the results of loan portfolio sorts in Table 7, indicate that the adverse effect of climate risk may be concentrated in a loan subsample characterized by long maturity and high exposure to climate risk. In fact, results reported in Panel C of Table 8 add to the credibility of this conjecture. In Panel C, we split the sample into high and low climate risk exposure depending on whether a firm's climate risk exposure is above the sample median. The direction of the result is generally consistent with expectation. TREND coefficients are positive in high climate risk category while they are negative in low climate risk subsample. However, the statistical significance is lost in specifications with more fixed effects and clustering of standard errors (columns 5 and 6). This result together with those in Panels A and B and Table 7, suggest that the adverse effect of climate risk is likely to be driven by a subsample of loans that are long-term, issued to poorly rated firms located in areas with high exposure to climate risk. We explore this conjecture in the next section.

4.3. Loan Subsample Driving the effect

In this section we examine the conjecture that the adverse effect of climate risk is mainly concentrated in long-term loans of poorly rated firms that are highly exposed to climate risk. We report the results of our regressions in Table 9. In Panel A, we estimate regression model (2) using a sample comprised of long-term loans issued to poorly rated firms that are highly exposed to climate risk. This subsample is an intersection of the three subsamples analyzed in Table 8. The coefficient on TREND is positive and statistically significant in all model specifications. The size of the coefficients is also relatively stable. This result implies a robust adverse impact of climate risk on the cost bank loans for poorly rated firms with high exposure to climate risk seeking a long-term loan and is consistent with our conjecture.

[Insert Table 9 about here]

However, there are a series of concerns with this analysis and the subsequent conclusion that the adverse effect of climate risk is driven by this subsample. For one, loan spreads of poorly rated firms, very much like their bond yield spreads, are very sensitive. In a regression setting, where loan or yield spreads are the dependent variable, generally the coefficients estimated for a non-investment sample suggest an amplification of the effect being studied. This amplification of the effect, sometimes, is not connected to any economic justification and is just simply an artifact of the sample that is comprised of poorly rated entities. Moreover, long-term loans also face a similar issue. Spreads on long-term loans (and bonds) are very sensitive and as a dependent variable in a regression, they could produce coefficient estimates that would imply a more pronounced effect. Therefore, our documented robust adverse effect of climate risk on a subsample of long-term loans issued to poorly rated firms that are highly exposed to climate risk may simply be the artifact of the sample. Hence, it is imperative to address this issue and provide more evidence consistent with our conclusion.

We address these issues in the Panels B through E of Table 9. We find that if any of the three characteristics of tis subsample (long maturity, poorly rated, and highly exposed to climate risk) is changed or excluded, the effect of climate risk becomes statistically insignificant. For example, our results in Panel B indicate that the effect of climate risk becomes statistically insignificant if the long maturity component is changed to short maturity. In other words, insignificant climate risk effect for a subsample of short-term loans issued to poorly rated firms with high climate risk exposure. Similarly, in Panel C, we replace the loans highly exposed to climate risk with those that have low exposure. We find that the effect of climate risk is insignificant for the resulting subsample, long-term loans of speculative rated firms with low exposure to climate risk. In Panel D, we focus on a subsample of long-term loans issued to firms with high credit quality but highly exposed to climate risk; and we find the effect is insignificant. Finally, Panel E reports the regression results for a subsample of short-term loans of highly rated firms with low climate risk exposure. As expected, the effect of climate risk is insignificant.

Results in Panels B and C alleviate the concern related to the sensitivity of loan spreads of poorly rated firms. Results in Panels C and D address the concern related to the sensitivity of the spreads on long-term loans. Collectively, the results in Panels B through E alleviate the concerns that the adverse effect of climate risk documented in Panel A is just an artifact of the subsample and that it is simply a manifestation of the sensitivity of the spreads on long-term loans of poorly rated firms. Overall, the results of this table suggest that the adverse effect of climate risk is mainly driven by a subsample of long-term loans issued to poorly rated firms that have high exposure to climate risk.

4.4. Food Industry Subsample

As discussed by Hong et al (2019), drought conditions have considerable negative impact on food industry. The reason is that the food industry is heavily dependent on water and hence significantly sensitive to drought. Therefore, firms in the food industry are likely to experience lower profits when facing adverse drought conditions. Given that our main measure of climate risk is rooted in drought condition, it follows that the effect of climate risk should be stronger among the borrowing firms in the food industry. Moreover, the results documented in the previous section imply that this stronger effect should be mainly driven by the poorly rated firms in the food industry that are highly exposed to climate risk and seek a long-term loan. However, the results of our analysis are inconsistent with these predictions. We find no marginal difference between firms in the "Food" industry and others irrespective how Food industry is defined and whether we use the long-term, poorly rated, and highly exposed subsample.[18] This insignificant result could be the artifact of our sample since there are only about 1,000 observations that belong to the Food industry. Alternatively, this result can perhaps be explained by the fact that lenders do not simply see much difference between firms in the Food industry and others. This interpretation would then be consistent with the financial market underreaction to climate risk documented by Hong et al (2019), and would reflect the fact that financial market has yet to fully understand and price all dimensions of climate risk.

5. Stern Review

In this section, we examine the role of investor attention in pricing of the climate risk in the loan spreads. Markets might not pay enough attention to risks that they have had little experience to deal with and digest, which could lead to market underreaction to that risk. Market inattentiveness to different types of value relevant information or risks is well documented in the literature (Hong et al., 2007, DellaVigna and Pollet, 2007; Cohen and Frazzini, 2008; Hong et al., 2019). To identify the effect of market attention on the pricing of climate risk in loan spreads, we follow Painter (2020) and conduct a quasi-natural experiment surrounding the release of the Stern Review. This is a 700-page report released for the government of United Kingdom and is the largest and most widely known and discussed report related to climate change and is commonly credited with substantially raising awareness to climate change.

[18] We do not report the results to save space. We use Fama-French 48 industry classification to define the Food industry. Our analysis separately considers FF industry classification codes 1 (Agriculture), 2 (Food Products), 1 and 2 together, and 1, 2, 3 (Soda), and 4 (Beer & Liquor) together.

The release of this report is unlikely to have affected the risk profile of the borrowing firms other than through increased awareness of climate risk. Thus, a significant rise in the cost of bank loan after the Stern Review suggests that lenders attention significantly affects the pricing of climate risk in the loan spreads. To isolate the effect of market attention, we restrict the sample to loans issued in two timeframes around the release of the Stern Report: a five-year and a ten-year window. We report the results in Table 10. In the first two columns, the interaction term between TREND and Stern is statistically insignificant, suggesting that lenders attention does not play any role in pricing of the climate risk in loan spreads.

[Insert Table 10 and Figure 2 about here]

On the one hand, this result is inconsistent with expectation and the findings in Painter (2020). On the other hand, we provide evidence in Section 4.3 that climate risk is mainly concentrated in a subsample of loans that are long-term, issued to poorly rated firms that are highly exposed to climate risk. Therefore, it would be imperative to examine if the cross-sectional variation in the effect of climate risk has any implications for this analysis. To investigate this issue, we split the sample into investment and non-investment categories and conduct our analysis for these two groups. Focusing on the investment category and the 10-year window, we find a statistically significant difference of about 7-bps (t-stat = 1.79) in the loan spread between long-term loans of poorly rated firms with high exposure to climate risk and all other loans in the non-investment category after the release of the Stern Review. This result is consistent with our earlier findings and highlight the significant cross-sectional heterogeneity in the effect of climate risk on the cost of bank loans. Figure 2 depicts the parallel trend between the examined subsample and all other loans. This figure shows that in 2006 subsequent to the release of the Stern Report the cost of bank loans substantially increases for poorly rated firms that are highly exposed to climate risk and seek long-term loans (group one in the figure) compared to all other loans (group zero in the figure).

However, for the narrower window of five years, the difference is statistically insignificant, suggesting a slow and gradual attention to climate risk by lenders. Results for the investment category are insignificant, irrespective of the time window, further signifying that the impact of climate risk is mainly driven by poorly rated firms. Overall, these results provide suggestive evidence on the slow and gradual attention of lenders to climate risk and they are consistent with the documented underreaction of financial market to climate risk by Hong et al. (2019).

6. Other Loan Contractual Features

Our results up to this point provide evidence that lenders view climate change as a risk factor and therefore charge a higher spread on loans issued to firms located in areas more exposed to this risk. However, as pointed out in prior research (Dennis et al., 2000; Goss and Roberts, 2011; among others) in addition to directly increasing the cost of loans, lenders have the option to change other contractual features of their loans to mitigate the risk associated with their borrowers. Specifically, they can issue more secured loans, shorten the maturity, reduce the size of the loan, increase up-front fees, and include more restrictive covenant in the loan contract. In this section, we focus on these contractual features of loans and test these predictions. We report the results in Table 11.

[Insert Table 11 about here]

In each panel of Table 11, we separately investigate the effect of climate risk on a contractual feature of a loan by estimating an augmented version of regression model (2) that uses that loan feature as the dependent variable. While the effect of climate risk on all these loan contractual features have the expected direction, with one exception, they are statistically insignificant. We find that lenders issue smaller loans and shorten loan maturity while they increase upfront fees, include more covenants in their loans, and are more likely to issue secured loans. However, only the increase in upfront fee is statistically significant.

Nonetheless, our results in Section 4.4.3 indicate that climate risk mainly driven by a subsample of loans that are long-term, issued to poorly rated firms that are in areas with high exposure to climate risk. It would be instructive to check whether this cross-section variation has also implications for our analysis of other contractual features of loans. Therefore, we run our analysis on this loan subsample. Results substantially improve and they are reported in Table 12.

[Insert Table 12 about here]

Results for this subsample indicate that, an increase in the climate risk exposure of a borrower is associated with a significant reduction in the size of the loan and an increase in the number of covenants included in the loan as well as the likelihood of issuing a secured loan by a lender. A one standard deviation increase in climate risk is associated with a decrease of 8.64% in the loan size, with about 14.3% increase in the number covenants, and with a 3% rise in the likelihood of issuing a secured loan. Overall, while these results provide suggestive evidence that climate risk affects other loan features, they support our earlier findings that the impact of climate risk is significantly stronger for long-term loans of poorly rated firms with high exposure to climate risk.

Moreover, results in Panel C of Table 11 and 12 suggest that the number of participants in a loan syndicate decreases as a borrowing firm's exposure to climate risk increases. While the direction of the effect is consistent with expectation, the effect of climate risk on the size of loan syndicate is statistically insignificant for stricter model specifications in Table 11 that uses the entire sample. However, in Table 12 that uses long-term loans of poorly rated firms with high climate risk exposure, this effect is significant for all specifications. A one standard deviation increase in climate risk is associated with a decrease of 8.14% in the number of lenders in the loan syndicate. This result signifies the fact that lenders do view climate change as a risk factor and is consistent with the findings in Chava (2014). Additionally, lower number of participants in a loan syndicate in and of itself could increase the cost of borrowing. As demonstrated by prior research (Merton, 1987; Heinkel et al., 2001), if a sufficiently large number of lenders avoid a borrowing firm, this firm would have fewer participants in its loan syndicate and would have to pay a higher spread on its loan and our findings confirm this prediction.

7. Conclusion

We provide empirical evidence supporting the idea that climate change is viewed as a risk factors by lenders and is priced in their loans. Our results are robust to different measures of climate risk and different model specifications. To alleviate the concern associated with the setup of our empirical design that determines a firm exposure to climate risk based on the state of its headquarter, we exploit the economic link between a firm and its customers. We present evidence that the exposure of a firm's customers to climate risk adversely affects that firm's cost of borrowing. Our subsample analyses show that the effect of climate risk is predominantly driven by a subsample of loans that are long-term, issued to poorly rated firms that have relatively high exposure to climate risk. Our evidence implies that the adverse effect of climate risk is insignificant for any other loan subsample that excludes any of these characteristics.

The analysis around the release of the Stern Report shows a significant increase in the loan spreads of the aforementioned loan subsample compared to others. However, this effect exists only for a 10-year window and vanishes for a shorter window of 5-year around the release of the report, suggesting a slow and gradual attention of lenders to the risk associated with climate change. Moreover, we find suggestive evidence that climate risk can affect other contractual features of loans. However, consistent with the our earlier findings, the documented effects — smaller loan size, decrease in the syndicate size, increase in the number of included covenants, and the rise in the probability of issuing a secured loan — are mainly driven by the same subsample; long-term loans issued to speculative rated firms that are highly exposed to climate risk.

As pointed out by Painter (2020) the debate about the exitance of climate change has no bearing on our study. However, while we do find an adverse impact of climate risk on loan spreads, our evidence indicates a slow and gradual increase in lenders' attention to this risk and that financial market has yet to fully understand and price all dimensions of climate risk. The results of this study suggest that further discussion and awareness about the consequences of climate change and the risk it entails would be beneficial to financial market's handling, understanding and pricing of this risk.

References

Allen, F., Carletti, E., Qian, J., & Valenzuela, P. (2013). Financial intermediation, markets, and alternative financial sectors. In Constantinides, G., Harris, M., Stulz, R. (Eds.), *Handbook of Economics of Finance*. Amsterdam: North-Holland.

Bansal, R., Kiku, D., & Ochoa, M. (2016). *Price of long-run temperature shifts in capital markets* (No. w22529). National Bureau of Economic Research.

Bernstein, A., Gustafson, M. T., & Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, *134*(2), 253-272.

Bradley, M., & Roberts, M. R. (2015). The structure and pricing of corporate debt covenants. *The Quarterly Journal of Finance*, *5*(02), 1550001.

Chaney, T., Sraer, D., & Thesmar, D. (2012). The collateral channel: How real estate shocks affect corporate investment. *American Economic Review*, *102*(6), 2381-2409.

Chang, X. S., Fu, K., Li, T., Tam, L., & Wong, G. (2018). Corporate environmental liabilities and capital structure. *Available at SSRN 3200991*.

Chava, S., Livdan, D., & Purnanandam, A. (2009). Do shareholder rights affect the cost of bank loans?. *The Review of Financial Studies*, *22*(8), 2973-3004.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, *60*(9), 2223-2247.

Cogan, D.G., 2008. Corporate Governance and Climate Change: *The Banking Sector*. Boston: Ceres, Inc.

Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, *63*(4), 1977-2011.

Coval, J. D., & Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance*, *54*(6), 2045-2073.

Dai, A. (2011). Drought under global warming: a review. *Wiley Interdisciplinary Reviews: Climate Change*, *2*(1), 45-65.

Davis, J. C., & Henderson, J. V. (2008). The agglomeration of headquarters. *Regional Science and Urban Economics*, *38*(5), 445-460.

DellaVigna, S., & Pollet, J. M. (2007). Demographics and industry returns. *American Economic Review*, *97*(5), 1667-1702.

Dennis, S., Nandy, D., & Sharpe, L. G. (2000). The determinants of contract terms in bank revolving credit agreements. *Journal of financial and quantitative analysis*, *35*(1), 87-110.

Graham, J. R., Li, S., & Qiu, J. (2008). Corporate misreporting and bank loan contracting. *Journal of Financial Economics*, *89*(1), 44-61.

Goss, A., & Roberts, G. S. (2011). The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance*, *35*(7), 1794-1810.

Heinkel, R., Kraus, A., & Zechner, J. (2001). The effect of green investment on corporate behavior. *Journal of financial and quantitative analysis*, *36*(4), 431-449.

Hilary, G., & Hui, K. W. (2009). Does religion matter in corporate decision making in America?. *Journal of financial economics*, *93*(3), 455-473.

Hong, H., Torous, W., & Valkanov, R. (2007). Do industries lead stock markets?. *Journal of Financial Economics*, *83*(2), 367-396.

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, *208*(1), 265-281.

Houston, J., & James, C. (1996). Bank information monopolies and the mix of private and public debt claims. *The Journal of Finance*, *51*(5), 1863-1889.

Ivković, Z., & Weisbenner, S. (2007). Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices. *The Review of Financial Studies*, *20*(4), 1327-1357.

Korniotis, G. M., & Kumar, A. (2013). State-level business cycles and local return predictability. *The Journal of Finance*, *68*(3), 1037-1096.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, *29*(2), 449-470.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The journal of finance*, *42*(3), 483-510.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, *135*(2), 468-482.

Palmer, W. C. (1965). *Meteorological drought* (Vol. 30). US Department of Commerce, Weather Bureau.

Pirinsky, C., & Wang, Q. (2006). Does corporate headquarters location matter for stock returns?. *The Journal of Finance*, *61*(4), 1991-2015.

Qian, J., & Strahan, P. E. (2007). How laws and institutions shape financial contracts: The case of bank loans. *The Journal of Finance*, *62*(6), 2803-2834.

Stern, N. (2008). The economics of climate change. *American Economic Review*, *98*(2), 1-37.

Truong, C., Nguyen, T. H., & Huynh, T. D. Drought and the Cost of Equity.

Tuzel, S., & Zhang, M. B. (2017). Local risk, local factors, and asset prices. *The Journal of Finance*, *72*(1), 325-370.

Table 1: Summary statistics

This table reports summary statistics of different variables from our main dataset constructed based on a cross-section of 40,006 different loan facilities (data source: LPC DealScan) issued to 6,267 unique firms headquartered in 48 U.S. mainland-states during the years 1986 to 2017. Table A.1 (appears in Appendices) provides detailed descriptions and sources of all variables.

VARIABLE	N	MEAN	SD	P10	P25	P50	P75	P90
SPREAD (bps)	40,006	174.430	121.959	40	87.5	150	250	325
MATURITY (Months)	38,754	46.544	22.931	12	33	51	60	72
DEAL ($M)	40,006	659	1420	30	85	250	700	1520
NLENDER	39,985	8.292	8.580	1	2	6	11	19
TOTALCOV	40,006	3.282	3.474	0	0	3	5	9
LN_UPFRONT	7,485	3.454	1.057	2.140	2.708	3.401	4.230	4.605
SECURE LOAN (Dummy)	26,690	0.680	0.466	0	0	1	1	1
NEGPDSI	40,006	-0.061	1.675	-2.219	-1.176	-0.143	0.950	2.101
TREND	40,006	-0.022	0.061	-0.099	-0.063	-0.031	0.030	0.063
DURATION (Days)	40,006	48.017	347.882	2	4	10	30	31
LN_AT	40,006	7.173	1.969	4.655	5.802	7.127	8.461	9.721
LEV Ratio	40,006	0.382	0.237	0.072	0.204	0.360	0.536	0.721
MTB	39,924	1.658	1.116	0.972	1.108	1.362	1.833	2.611
ROA	39,981	0.033	0.357	-0.044	0.008	0.039	0.076	0.123
TERMLOAN	40,006	0.270	0.444	0	0	0	1	1

.

Table 2: Univariate analysis

In Panel A of this table, we present pairwise correlations between our key dependent variable, SPREAD, and two of our key measures of climate risk (key independent variable), NEGPDSI and TREND. Panel B presents mean t-test results of SPREAD from two extreme groups (Q1-first quartile and Q4-fourth quartile) of NEGPDSI and TREND. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Panel A: Pairwise correlation				
VARIABLES		(NEGPDSI)	(TREND)	(SPREAD)
NEGPDSI		1.000		
TREND		0.344***	1.000	
SPREAD		0.083***	0.048***	1.000
Panel B: Loan Portfolios				
Basis	Q1	Q4	Difference	t-stats
NEGPDSI	166.487	187.508	21.021***	12.056
TREND	170.192	185.406	15.214***	8.679

Table 3: Loan Spread and PDSI

This table presents Log_Spread (labeled as ln_allindrawn here), as a function of Negative PDSI score (NEGPDSI) and controls. Columns (1), (2), (3) include mandatory Year fixed effect and Industry (two-digits SIC) fixed effect. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln_allindrawn	ln_allindrawn	ln_allindrawn	ln_allindrawn	ln_allindrawn	ln_allindrawn
NEGPDSI	0.010***	0.010***	0.010***	0.009***	0.009***	0.009***
	(5.64)	(3.86)	(3.41)	(4.99)	(3.52)	(2.74)
Log (Asset)	-0.183***	-0.183***	-0.183***	-0.174***	-0.174***	-0.174***
	(-77.13)	(-25.29)	(-26.38)	(-62.23)	(-20.76)	(-18.49)
LEV Ratio	0.502***	0.502***	0.502***	0.464***	0.464***	0.464***
	(33.22)	(17.46)	(19.88)	(30.58)	(16.64)	(20.04)
MTB	-0.085***	-0.085***	-0.085***	-0.088***	-0.088***	-0.088***
	(-6.53)	(-5.40)	(-3.00)	(-6.54)	(-5.65)	(-3.24)
ROA	-0.065	-0.065	-0.065	-0.046	-0.046	-0.046
	(-0.81)	(-0.81)	(-0.93)	(-0.71)	(-0.71)	(-0.79)
TERMLOAN	-0.041**	-0.041*	-0.041**	-0.039**	-0.039*	-0.039**
	(-2.17)	(-1.83)	(-2.28)	(-1.96)	(-1.73)	(-2.39)
REVOLVER	-0.385***	-0.385***	-0.385***	-0.341***	-0.341***	-0.341***
	(-19.46)	(-16.01)	(-18.05)	(-16.68)	(-14.27)	(-17.04)
MERGER	0.196***	0.196***	0.196***	0.187***	0.187***	0.187***
	(14.72)	(10.27)	(10.01)	(14.13)	(10.17)	(10.27)
LBO	0.996***	0.996***	0.996***	0.848***	0.848***	0.848***
	(27.12)	(16.65)	(20.33)	(23.14)	(14.73)	(17.05)
CORPPURP	0.073***	0.073***	0.073***	0.087***	0.087***	0.087***
	(6.19)	(4.50)	(4.35)	(7.53)	(5.47)	(5.69)
DEBTPAY	0.205***	0.205***	0.205***	0.197***	0.197***	0.197***
	(14.88)	(11.09)	(11.27)	(14.40)	(10.81)	(10.68)
OTHERTYPE	-0.634***	-0.634***	-0.634***	-0.586***	-0.586***	-0.586***
	(-27.40)	(-21.22)	(-19.42)	(-24.71)	(-19.54)	(-19.41)
WORKCAP	0.134***	0.134***	0.134***	0.141***	0.141***	0.141***
	(10.42)	(7.26)	(6.38)	(11.17)	(7.93)	(7.03)
Constant	6.380***	6.380***	6.380***	6.301***	6.301***	6.301***
	(159.98)	(98.44)	(77.05)	(146.10)	(88.69)	(60.44)
Observations	39,900	39,900	39,900	38,600	38,600	38,600
Adjusted R-squared	0.503	0.503	0.503	0.548	0.548	0.548
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 4: Loan Spread and TREND

This table presents Log_Spread (labeled as ln_allindrawn here), as a function of long-term climate change trend (TREND) and controls. Columns (1), (2), (3) consider mandatory Year fixed effect and Industry (two-digits SIC) fixed effect. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln_allindrawn	ln_allindrawn	ln_allindrawn	ln_allindrawn	ln_allindrawn	ln_allindrawn
TREND	0.306***	0.306***	0.306**	0.214***	0.214**	0.214*
	(6.72)	(2.96)	(2.46)	(4.58)	(2.02)	(1.73)
Log (Asset)	-0.183***	-0.183***	-0.183***	-0.174***	-0.174***	-0.174***
	(-77.09)	(-25.32)	(-26.06)	(-62.11)	(-20.72)	(-18.25)
LEV Ratio	0.503***	0.503***	0.503***	0.465***	0.465***	0.465***
	(33.34)	(17.59)	(20.26)	(30.64)	(16.70)	(20.28)
MTB	-0.086***	-0.086***	-0.086***	-0.088***	-0.088***	-0.088***
	(-6.56)	(-5.44)	(-3.05)	(-6.55)	(-5.67)	(-3.26)
ROA	-0.064	-0.064	-0.064	-0.046	-0.046	-0.046
	(-0.80)	(-0.80)	(-0.92)	(-0.70)	(-0.70)	(-0.78)
TERMLOAN	-0.041**	-0.041*	-0.041**	-0.039**	-0.039*	-0.039**
	(-2.16)	(-1.82)	(-2.28)	(-1.97)	(-1.74)	(-2.44)
REVOLVER	-0.384***	-0.384***	-0.384***	-0.341***	-0.341***	-0.341***
	(-19.45)	(-15.96)	(-18.16)	(-16.69)	(-14.27)	(-17.28)
MERGER	0.197***	0.197***	0.197***	0.188***	0.188***	0.188***
	(14.77)	(10.29)	(10.14)	(14.16)	(10.19)	(10.37)
LBO	0.998***	0.998***	0.998***	0.850***	0.850***	0.850***
	(27.14)	(16.64)	(20.19)	(23.19)	(14.71)	(16.91)
CORPPURP	0.073***	0.073***	0.073***	0.088***	0.088***	0.088***
	(6.19)	(4.49)	(4.41)	(7.54)	(5.47)	(5.75)
DEBTPAY	0.206***	0.206***	0.206***	0.198***	0.198***	0.198***
	(14.96)	(11.14)	(11.38)	(14.45)	(10.83)	(10.79)
OTHERTYPE	-0.634***	-0.634***	-0.634***	-0.586***	-0.586***	-0.586***
	(-27.39)	(-21.21)	(-19.58)	(-24.72)	(-19.56)	(-19.61)
WORKCAP	0.134***	0.134***	0.134***	0.141***	0.141***	0.141***
	(10.45)	(7.29)	(6.45)	(11.20)	(7.95)	(7.08)
Constant	6.384***	6.384***	6.384***	6.304***	6.304***	6.304***
	(160.34)	(99.03)	(75.45)	(146.38)	(89.17)	(59.74)
Observations	39,900	39,900	39,900	38,600	38,600	38,600
Adjusted R-squared	0.503	0.503	0.503	0.548	0.548	0.548
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 5: Loan Spread and natural hazards intensity

In this table, as a robustness check of our main results, we present cost of bank loan, Log (Spread), as a function of intensity (or damages) due to natural hazards (likely to be influenced by climate change) from SHELDUS database, Log (Duration) in Panel A, Property Damage in Panel B, and Crop Damage in Panel C, and controls. Durations are in days, Damages (Property or Crop) are in billion dollars and adjusted for 2017. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Panel A: Spread and Duration (Days)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log (Duration)	0.014***	0.014***	0.014***	0.012***	0.012***	0.012**
	(5.99)	(3.49)	(3.09)	(4.82)	(2.85)	(2.60)
Constant	6.347***	6.347***	6.347***	6.274***	6.274***	6.274***
	(158.06)	(95.57)	(71.98)	(144.34)	(85.72)	(58.43)
Observations	39,900	39,900	39,900	38,600	38,600	38,600
Adjusted R-squared	0.503	0.503	0.503	0.548	0.548	0.548
Panel B: Spread and Property Damage, $B (2017 Adjusted)						
Property_damage	0.003***	0.003***	0.003***	0.002***	0.002***	0.002***
	(4.90)	(3.80)	(5.31)	(3.85)	(3.06)	(2.78)
Constant	6.378***	6.378***	6.378***	6.300***	6.300***	6.300***
	(159.74)	(98.32)	(77.74)	(145.73)	(88.49)	(60.48)
Observations	39,900	39,900	39,900	38,600	38,600	38,600
Adjusted R-squared	0.503	0.503	0.503	0.548	0.548	0.548
Panel C: Spread and Crop Damage, $B (2017 Adjusted)						
Crop_damage	0.024***	0.024***	0.024***	0.022***	0.022***	0.022***
	(5.56)	(3.65)	(4.92)	(4.98)	(3.35)	(4.73)
Constant	6.374***	6.374***	6.374***	6.295***	6.295***	6.295***
	(159.55)	(98.12)	(76.57)	(145.62)	(88.32)	(59.94)
Observations	39,900	39,900	39,900	38,600	38,600	38,600
Adjusted R-squared	0.503	0.503	0.503	0.549	0.549	0.549
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T & P FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Control	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 6: Loan Spread and Customer climate risk exposure

This table presents Log_Spread (labeled as ln_allindrawn), as a function of TREND_CSTMR (TREND at customers' global end) and controls. Columns (1), (2), (3) consider mandatory Year fixed effect and Industry (two-digits SIC) fixed effect. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and country, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively. Sample period for this analysis is 1986-2014 rather than 1986-2017 (as global PDSI data is not available beyond 2014). Number of observations is relatively higher than our other similar analyses with NEGPDSI and TREND (as one particular firm can be operated in more than one country while in other analyses every firm has obviously one headquarter location only).

VARIABLES	(1) ln_allindrawn	(2) ln_allindrawn	(3) ln_allindrawn	(4) ln_allindrawn	(5) ln_allindrawn	(6) ln_allindrawn
TREND_CSTMR	0.157***	0.157*	0.157*	0.155***	0.155**	0.155**
	(3.15)	(1.86)	(1.81)	(3.26)	(2.06)	(2.49)
Log (Asset)	-0.195***	-0.195***	-0.195***	-0.186***	-0.186***	-0.186***
	(-93.09)	(-15.43)	(-16.56)	(-73.77)	(-12.45)	(-13.19)
LEV Ratio	0.555***	0.555***	0.555***	0.511***	0.511***	0.511***
	(42.92)	(11.58)	(10.86)	(38.82)	(10.84)	(10.42)
MTB	-0.063***	-0.063***	-0.063***	-0.065***	-0.065***	-0.065***
	(-6.04)	(-3.38)	(-3.98)	(-6.28)	(-3.69)	(-4.28)
ROA	-0.822***	-0.822***	-0.822***	-0.755***	-0.755***	-0.755***
	(-11.47)	(-6.20)	(-6.89)	(-10.38)	(-5.63)	(-6.37)
TERMLOAN	-0.055***	-0.055*	-0.055*	-0.068***	-0.068**	.068**
	(-3.29)	(-1.71)	(-1.92)	(-3.90)	(-2.10)	(-2.23)
REVOLVER	-0.442***	-0.442***	-0.442***	-0.417***	-0.417***	-0.417***
	(-25.26)	(-12.82)	(-11.89)	(-23.00)	(-11.76)	(-9.96)
MERGER	0.181***	0.181***	0.181***	0.183***	0.183***	0.183***
	(16.79)	(5.89)	(4.93)	(17.05)	(6.25)	(5.53)
LBO	1.045***	1.045***	1.045***	0.929***	0.929***	0.929***
	(29.47)	(10.15)	(11.51)	(26.43)	(9.06)	(9.09)
CORPPURP	0.074***	0.074***	0.074***	0.087***	0.087***	0.087***
	(7.84)	(3.03)	(3.14)	(9.31)	(3.58)	(3.61)
DEBTPAY	0.189***	0.189***	0.189***	0.173***	0.173***	0.173***
	(17.25)	(6.72)	(6.18)	(15.91)	(6.19)	(4.90)
OTHERTYPE	-0.695***	-0.695***	-0.695***	-0.665***	-0.665***	-0.665***
	(-34.94)	(-15.67)	(-15.32)	(-32.43)	(-14.38)	(-13.15)
WORKCAP	0.152***	0.152***	0.152***	0.162***	0.162***	0.162***
	(14.02)	(4.94)	(5.67)	(15.17)	(5.24)	(5.92)
Constant	6.408***	6.408***	6.408***	6.346***	6.346***	6.346***
	(199.39)	(63.29)	(68.26)	(183.86)	(55.45)	(58.51)
Observations	58,972	58,972	58,972	57,113	57,113	57,113
Adjusted R-squared	0.545	0.545	0.545	0.596	0.596	0.596
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
Country Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 7: Double-sorting spread based on maturity and climate change

In this table we present how spread of bank loan varies with loan maturity (denoted by Ts) and firm's climate change exposure (denoted by Qs). Since firms can be susceptible to a long-term business risk if climate change exposure is higher, lenders (banks) also should penalize them for the loans with longer maturities. Here we report results from independently sorting of loan spreads based on maturity and TREND. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Double Sorting Spread by Maturity (T) and Trend (Q)

	Q1 (Low climate exposure)	Q2	Q3	Q4 (High climate exposure)
T1 (Low Maturity)	139.416	147.244	156.702	156.961
T2	187.017	194.227	189.222	200.400
T3	158.736	142.024	165.811	175.133
T4 (High Maturity)	220.790	205.240	226.708	231.927

	Difference	t-statistics
T4, Q4 – T1, Q1	92.511***	22.360
T4, Q4 – T4, Q1	11.137**	2.346
T4, Q4 - T1, Q4	74.966***	18.001
T4, Q1 - T1, Q1	81.374***	19.738
T1, Q4 - T1, Q1	17.545***	4.4905

Table 8: Loan Subsamples

In this table we present a series of subsample analyses based on our original analysis of log (spread) as a function of TREND and controls (Table 4). Panel A1 and A2 present Investment Grade vs. Noninvestment Grade, Panel B1 and B2 present Long Maturity (T3 and T4) vs. Short Maturity (T1 and T2), and Panel C1 and C2 present Higher Exposure (Q3 and Q4) vs. Lower Exposure (Q1 and Q2) subsamples. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A1: Investment Grade						
TREND	0.140	0.140	0.140	0.159	0.159	0.159
	(1.23)	(0.58)	(0.59)	(1.35)	(0.64)	(0.64)
CONSTANT	6.126***	6.126***	6.126***	6.022***	6.022***	6.022***
	(76.49)	(47.67)	(54.53)	(71.49)	(45.92)	(49.16)
N	7,578	7,578	7,578	7,326	7,326	7,326
ADJ. R^2	0.564	0.564	0.564	0.598	0.598	0.598
Panel A2: Noninvestment Grade						
TREND	0.370***	0.370***	0.370***	0.273***	0.273***	0.273***
	(7.99)	(4.08)	(3.56)	(5.80)	(2.99)	(3.63)
CONSTANT	6.150***	6.150***	6.150***	6.117***	6.117***	6.117***
	(154.19)	(101.83)	(83.81)	(141.97)	(93.08)	(68.57)
N	31,071	31,071	31,071	30,040	30,040	30,040
ADJ. R^2	0.380	0.380	0.380	0.444	0.444	0.444
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B1: Long Maturity (T3 and T4)						
TREND	0.296***	0.296**	0.296**	0.177***	0.177	0.177
	(4.84)	(2.44)	(2.57)	(2.88)	(1.45)	(1.44)
CONSTANT	6.287***	6.287***	6.287***	6.245***	6.245***	6.245***
	(133.42)	(67.20)	(53.51)	(127.56)	(59.18)	(43.67)
N	19,326	19,326	19,326	18,737	18,737	18,737
ADJ. R^2	0.522	0.522	0.522	0.576	0.576	0.576
Panel B2: Short Maturity (T1 and T2)						
TREND	0.228***	0.228**	0.228*	0.169**	0.169	0.169
	(3.45)	(1.99)	(1.65)	(2.40)	(1.39)	(1.18)
CONSTANT	6.226***	6.226***	6.226***	6.178***	6.178***	6.178***
	(84.24)	(73.51)	(75.50)	(80.37)	(71.94)	(58.89)
N	19,323	19,323	19,323	18,541	18,541	18,541
ADJ. R^2	0.534	0.534	0.534	0.569	0.569	0.569
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C1: Higher Exposure (Q3 and Q4)						
TREND	0.369***	0.369*	0.369	0.286**	0.286	0.286
	(3.42)	(1.72)	(1.39)	(2.55)	(1.28)	(1.28)
CONSTANT	6.346***	6.346***	6.346***	6.248***	6.248***	6.248***
	(120.77)	(67.65)	(58.28)	(105.92)	(57.77)	(48.52)
N	19,314	19,314	19,314	18,654	18,654	18,654
ADJ. R^2	0.493	0.493	0.493	0.541	0.541	0.541
Panel C2: Lower Exposure (Q1 and Q2)						
TREND	-0.360***	-0.360	-0.360	-0.289**	-0.289	-0.289
	(-2.91)	(-1.50)	(-1.02)	(-2.28)	(-1.21)	(-0.86)
CONSTANT	6.428***	6.428***	6.428***	6.411***	6.411***	6.411***
	(149.74)	(94.57)	(89.17)	(144.41)	(92.17)	(101.41)
N	19,337	19,337	19,337	18,651	18,651	18,651
ADJ. R^2	0.535	0.535	0.535	0.583	0.583	0.583
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 9: Loan Subsample Driving the effect

In this table, we present a series of subsample analyses. Panel A presents High Exposure (Q3 and Q4), Long Maturity (T3 and T4) and Noninvestment subsample. Panel B presents High Exposure (Q3 and Q4), Short Maturity (T1 and T2) and Noninvestment subsample. Panel C presents Low Exposure (Q1 and Q2), Long Maturity (T3 and T4) and Noninvestment subsample. Panel D presents High Exposure (Q3 and Q4), Long Maturity (T3 and T4) and Investment subsample. Panel E presents Low Exposure (Q1 and Q2), Short Maturity (T1 and T2) and Investment subsample. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High Exposure (Q3 and Q4), Long Maturity (T3 and T4), Noninvestment						
TREND	0.406***	0.406*	0.406	0.366**	0.366*	0.366*
	(2.87)	(1.81)	(1.51)	(2.57)	(1.64)	(1.87)
CONSTANT	6.027***	6.027***	6.027***	5.976***	5.976***	5.976***
	(100.92)	(51.28)	(44.03)	(91.16)	(42.44)	(38.45)
N	8,327	8,327	8,327	8,017	8,017	8,017
ADJ. R^2	0.411	0.411	0.411	0.484	0.484	0.484
Panel B: High Exposure (Q3 and Q4), Short Maturity (T1 and T2), Noninvestment						
TREND	0.370**	0.370	0.370	0.184	0.184	0.184
	(2.27)	(1.54)	(1.14)	(1.04)	(0.72)	(0.63)
CONSTANT	5.897***	5.897***	5.897***	5.841***	5.841***	5.841***
	(61.53)	(55.74)	(57.34)	(55.84)	(52.00)	(41.00)
N	7,473	7,473	7,473	7,080	7,080	7,080
ADJ. R^2	0.400	0.400	0.400	0.454	0.454	0.454
Panel C: Low Exposure (Q1 and Q2), Long Maturity (T3 and T4), Noninvestment						
TREND	-0.347**	-0.347	-0.347	-0.262	-0.262	-0.262
	(-2.17)	(-1.42)	(-1.13)	(-1.61)	(-1.07)	(-0.95)
CONSTANT	6.078***	6.078***	6.078***	6.104***	6.104***	6.104***
	(102.26)	(76.45)	(81.27)	(95.07)	(74.91)	(86.32)
N	7,917	7,917	7,917	7,608	7,608	7,608
ADJ. R^2	0.457	0.457	0.457	0.524	0.524	0.524
Panel D: High Exposure (Q3 and Q4), Long Maturity (T3 and T4), Investment						
TREND	0.402	0.402	0.402	0.123	0.123	0.123
	(0.92)	(0.63)	(0.85)	(0.26)	(0.18)	(0.23)
CONSTANT	6.237***	6.237***	6.237***	6.084***	6.084***	6.084***
	(35.67)	(26.93)	(27.40)	(30.36)	(25.09)	(21.28)
N	1,428	1,428	1,428	1,350	1,350	1,350
ADJ. R^2	0.623	0.623	0.623	0.654	0.654	0.654
Panel E: Low Exposure (Q1 and Q2), Short Maturity (T1 and T2), Investment						
TREND	-0.289	-0.289	-0.289	-0.248	-0.248	-0.248
	(-0.68)	(-0.44)	(-0.34)	(-0.54)	(-0.34)	(-0.28)
CONSTANT	6.015***	6.015***	6.015***	6.106***	6.106***	6.106***
	(37.13)	(28.53)	(38.00)	(34.78)	(26.57)	(32.14)
N	2,415	2,415	2,415	2,304	2,304	2,304
ADJ. R^2	0.597	0.597	0.597	0.626	0.626	0.626
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 10: Difference-in-Difference

This table presents Difference-in-Difference (DiD) results of log (spread) around Stern Review (2006) for our entire sample (takes TREND interacted with Stern dummy as key independent variable), and Noninvestment and Investment subsamples (takes High Exposure, Long Maturity and Stern dummies interacted together as key independent variable). A 10-year window uses sample period 2002-2011 and a 5-year window uses sample period 2004-2008. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	Entire Sample		Non-Investment		Investment	
	10 years	5 years	10 years	5 years	10 years	5 years
TREND * Stern	-0.219	-0.011				
	(-0.89)	(-0.05)				
T34 *Q34*Stern			0.067*	0.103	-0.033	0.074
			(1.79)	(1.49)	(-0.58)	(0.80)
T34*Stern			-0.008	0.036	0.033	-0.070
			(-0.26)	(0.68)	(0.64)	(-1.37)
Q34*Stern			-0.042	-0.086*	-0.105**	-0.181**
			(-1.16)	(-1.74)	(-2.40)	(-2.06)
T34*Q34			-0.012	-0.032	-0.025	-0.084
			(-0.47)	(-0.99)	(-0.52)	(-1.21)
Q34			0.038	0.068***	0.091*	0.117*
			(1.66)	(2.94)	(2.00)	(1.69)
T34			-0.127***	-0.149***	-0.109***	-0.065
			(-5.82)	(-5.07)	(-2.81)	(-1.38)
CONSTANT	6.305***	6.404***	6.007***	6.055***	6.123***	5.988***
	(45.50)	(32.86)	(49.32)	(38.48)	(32.89)	(25.73)
N	14,229	7,625	10,662	5,715	3,535	1,888
ADJ. R2	0.588	0.574	0.457	0.438	0.664	0.525
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	Yes	Yes	Yes	Yes	Yes	Yes
State Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Other contractual features of loans (entire sample)

This table presents different contractual features of a loan as a function of long-term climate change trend (TREND) and controls. Panels A to Panel F present results for Deal Amount, Maturity, Number of Lenders in Loan Syndicate, Upfront Fee, Total Covenants, and Secured Loans as dependent variables, respectively. In Panel A to Panel D dependent variables are log-transformed. Columns (1), (2), (3) include mandatory Year fixed effect and Industry (two-digits SIC) fixed effect. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Deal Amount						
TREND	-0.326***	-0.326*	-0.326	-0.265***	-0.265	-0.265
	(-4.41)	(-1.94)	(-1.05)	(-3.53)	(-1.63)	(-0.92)
N	39,900	39,900	39,900	38,600	38,600	38,600
ADJ. R^2	0.683	0.683	0.683	0.710	0.710	0.710
Panel B: Maturity						
TREND	-0.071*	-0.071	-0.071	-0.068	-0.068	-0.068
	(-1.72)	(-1.18)	(-0.76)	(-1.63)	(-1.14)	(-1.18)
N	38,651	38,651	38,651	37,457	37,457	37,457
ADJ. R^2	0.466	0.466	0.466	0.497	0.497	0.497
Panel C: Number of Lenders in the Loan Syndicate						
TREND	-0.449***	-0.449***	-0.449	-0.353***	-0.353***	-0.353
	(-6.52)	(-3.31)	(-1.28)	(-5.04)	(-2.75)	(-1.17)
N	39,879	39,879	39,879	38,600	38,600	38,600
ADJ. R^2	0.367	0.367	0.367	0.423	0.423	0.423
Panel D: Upfront Fee						
TREND	0.783***	0.783***	0.783***	0.511***	0.511**	0.511**
	(4.47)	(3.50)	(3.47)	(2.68)	(2.09)	(2.59)
N	7,462	7,462	7,462	6,964	6,964	6,964
ADJ. R^2	0.252	0.252	0.252	0.325	0.325	0.325
Panel E: Total Covenants						
TREND	0.484**	0.484	0.484	0.563**	0.563	0.563
	(1.97)	(1.07)	(1.12)	(2.18)	(1.23)	(1.42)
N	39,900	39,900	39,900	38,600	38,600	38,600
ADJ. R^2	0.288	0.288	0.288	0.343	0.343	0.343
Panel F: Secured Loan						
TREND	0.140***	0.140	0.140	0.099**	0.099	0.099
	(3.50)	(1.62)	(1.34)	(2.33)	(1.09)	(0.91)
N	26,623	26,623	26,623	25,770	25,770	25,770
ADJ. R^2	0.285	0.285	0.285	0.323	0.323	0.323
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

Table 12: Other contractual features of loans for subsample

This table presents the results of studying different contractual features of loans as a function of long-term climate change trend (TREND) for a subsample of long-term loans, issued to poorly rated firms with high exposure to climate risk. Panel A to Panel F present results for Deal Amount, Maturity, Number of Lenders in Loan Syndicate, Upfront Fee, Total Covenants, and Secured Loans as dependent variables, respectively. In Panel A to Panel D dependent variables are log-transformed. Columns (1), (2), (3) use mandatory Year fixed effect and Industry (two-digits SIC) fixed effect. In column (1) we use robust standard errors, in column (2) we cluster standard errors by firm, in column (3) we use two-way clustering of standard errors by firm and state, and in columns (4) to (6) we repeat the models (1) to (3) with added Bank (Lending) fixed effects. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Deal Amount						
TREND	-1.684***	-1.684***	-1.684***	-1.416***	-1.416***	-1.416***
	(-6.96)	(-3.91)	(-4.44)	(-5.78)	(-3.37)	(-3.77)
N	8,327	8,327	8,327	8,017	8,017	8,017
ADJ. R^2	0.663	0.663	0.663	0.700	0.700	0.700
Panel B: Maturity						
TREND	0.010	0.010	0.010	-0.016	-0.016	-0.016
	(0.26)	(0.20)	(0.21)	(-0.42)	(-0.34)	(-0.41)
N	8,327	8,327	8,327	8,017	8,017	8,017
ADJ. R^2	0.271	0.271	0.271	0.333	0.333	0.333
Panel C: Number of Lenders in the Loan Syndicate						
TREND	-1.642***	-1.642***	-1.642***	-1.335***	-1.335***	-1.335***
	(-6.96)	(-4.38)	(-3.78)	(-5.62)	(-3.76)	(-3.47)
N	8,320	8,320	8,320	8,017	8,017	8,017
ADJ. R^2	0.314	0.314	0.314	0.395	0.395	0.395
Panel D: Upfront Fee						
TREND	0.307	0.307	0.307	-0.895	-0.895	-0.895
	(0.48)	(0.41)	(0.41)	(-1.27)	(-1.12)	(-1.35)
N	1,629	1,629	1,629	1,485	1,485	1,485
ADJ. R^2	0.242	0.242	0.242	0.335	0.335	0.335
Panel E: Total Covenants						
TREND	2.428**	2.428	2.428	2.342**	2.342	2.342*
	(2.45)	(1.46)	(1.66)	(2.27)	(1.42)	(1.77)
N	8,327	8,327	8,327	8,017	8,017	8,017
ADJ. R^2	0.304	0.304	0.304	0.374	0.374	0.374
Panel F: Secured Loan						
TREND	0.460***	0.460**	0.460**	0.487***	0.487**	0.487**
	(3.40)	(2.02)	(2.54)	(3.38)	(2.02)	(2.64)
N	6,313	6,313	6,313	6,075	6,075	6,075
ADJ. R2	0.235	0.235	0.235	0.281	0.281	0.281
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Loan T&P FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes

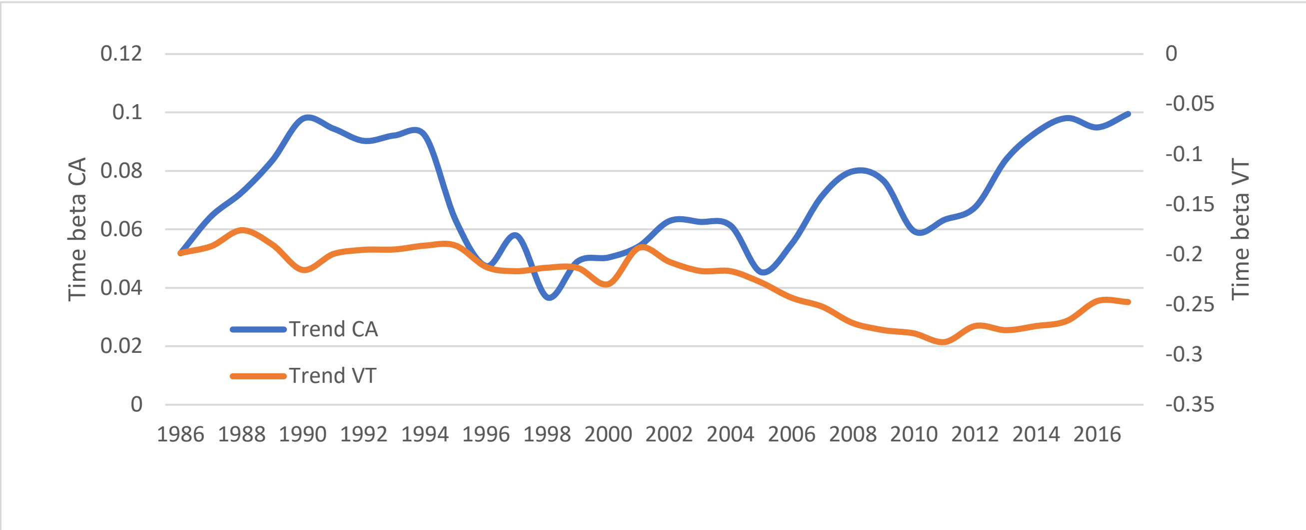
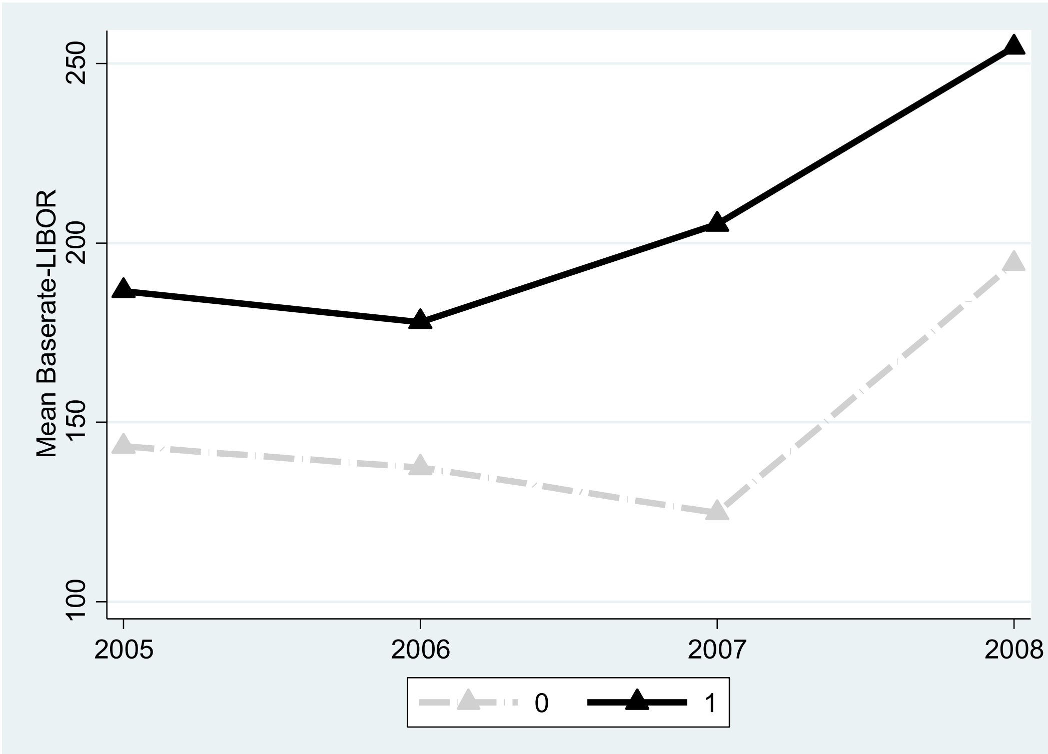


Figure 1: Historical trends of drought (CA vs. VT)

This figure compares the evolution of the long-term climate change trends of the U.S. state with the highest drought exposure, California (CA), and the state with the lowest drought exposure, Vermont (VT). Every point is determined from an AR(1) model: $\boldsymbol{PDSI_{s,t} = a + b * Time_s + c * PDSI_{s,t-1} + \varepsilon_{s,t}}$ using monthly frequency state-level historical PDSI data extending back to 1895.The higher value of "Time beta" indicates the higher exposure to climate change risk for the firms located in a state.

Figure 2: Movements in SPREAD following the Stern Review (2006)



This figure presents the difference in the loan spread following the Stern Review (2006). The group-1 (solid line) takes the value of 1 if the observation belongs to the subsample of long-term loans of poorly rated firms with high climate risk exposure and zero otherwise (dashed line).

Appendices

Table A.1: Variable Definitions

Variable	Definition	Source
NEGPDSI	Negative Palmer Drought Severity Index (PDSI); $NEGPDSI = -1 * PDSI$	NOAA's National Climatic Data Center (NCDC); www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers
TREND	Negative time trend coefficient (times 1,000) of an AR1 model extends back to 1895 for each state at each point of sample period using monthly frequency data; $TREND = -b * 1{,}000$	AR (1) Model: $PDSI_{s,t} = a + b * Time_s + c * PDSI_{s,t-1} + \varepsilon_{s,t}$
TREND_CSTMR	TREND determined from firms' customer segmentation locations (countries)	
Log (Duration)	The observed number of days of climate change related natural hazards (aggregated to state level); log-transformed	SHELDUS (Arizona State University); https://cemhs.asu.edu/sheldus
Log (Spread)	The interest amount paid by borrowers annually over LIBOR in basis points; log-transformed	LPC DealScan; $Log\ (Spread) = log\ (allindrawn)$
Log (Deal Amount)	Total Deal Amount; log-transformed	LPC DealScan; $Log\ (Deal\ Amount) = log\ (dealamount)$
Log (Lenders)	Number of Lenders in loan syndication; log-transformed	LPC DealScan; $Log\ (Lenders) = log\ (nlenders)$
Log (Maturity)	Maturity of loan in months; log-transformed	LPC DealScan; $Log\ (Maturity) = log\ (maturity)$
Total Covenants	Total number of Financial and General Covenants in loan contracts	LPC DealScan; $Total\ Covenants = gencov + fincov$
Log (Upfront Fee)	Upfront fee paid by borrowers for loans; log-transformed	LPC DealScan; $Log\ (Upfrontfee) = log\ (\frac{upfrfee_{min} + upfrfee_{max}}{2})$
Secured Loan	Dummy (=1, if the loan is secured, =0 if the loan is not secured)	LPC DealScan
Log (Asset)	Total Asset; log-transformed	COMPUSTAT; $Log\ (Asset) = log\ (at)$
LEV Ratio	Total debt over Asset	COMPUSTAT; $Lev\ Ratio = (dlc + dlt)/at$
MTB	Market to Book value	COMPUSTAT; $MTB = (prcc_f * csho + lt)/(ceq + lt)$
ROA	Return on Assets	COMPUSTAT; $ROA = lb/at$
TERMLOAN	Loan type dummy	LPC DealScan
REVOLVER	Loan type dummy	LPC DealScan
OTHERTYPE	Loan type dummy	LPC DealScan
CORPPURP	Loan purpose dummy	LPC DealScan
WORKCAP	Loan purpose dummy	LPC DealScan
DEBTPAY	Loan purpose dummy	LPC DealScan
LBO	Loan purpose dummy	LPC DealScan
MERGER	Loan purpose dummy	LPC DealScan
Stern	Dummy (=1, if year is later than 2006, = 0 otherwise)	
T34	Dummy (=1, if loan maturity is above 50% of the sample, =0 otherwise)	
T12	Dummy (=1, if loan maturity is below 50% of the sample, =0 otherwise)	
Q34	Dummy (=1, if climate exposure is above 50% of the sample, =0 otherwise)	
Q12	Dummy (=1, if climate exposure is below 50% of the sample, =0 otherwise)	
Investment	Dummy (=1, if S&P credit rating is **BBB-** or above, =0 otherwise)	
Noninvestment	Dummy (=1, if S&P credit rating is below **BBB-**, =0 otherwise)	

Table A.2: AR(1) model summary

This table presents the summary of our AR(1) model: $\boldsymbol{PDSI_{s,t} = a + b * Time_s + c * PDSI_{s,t-1} + \varepsilon_{s,t}}$. We use monthly state-level PDSI data extends back to 1895 to produce time-beta (indication of long-term climate change trend) for each state and later we convert them to yearly data for our main analyses. Here we report the values based on the beginning year of our sample period (1986). The states appear in the upper part of the list (marked with higher ranks) are having relatively higher long-term climate change exposure according to our model and vice-versa.

RANK	STATE	Constant β	TIME β	Adj. R^2
1	CALIFORNIA	0.041890077	0.071093	0.800210357
2	FLORIDA	0.045965944	0.06378	0.793352842
3	NEW JERSEY	0.038899709	0.061901	0.732830107
4	MONTANA	0.063882873	0.05957	0.869851112
5	CONNECTICUT	0.02851636	0.0447	0.692309678
6	DELAWARE	0.007264971	0.041048	0.754312635
7	WYOMING	0.042410329	0.038327	0.904199481
8	UTAH	0.037156258	0.035555	0.879621983
9	ARIZONA	0.022116868	0.033218	0.873995245
10	COLORADO	0.040159263	0.03206	0.888762891
11	NEVADA	0.0095003	0.027769	0.867517412
12	NORTH DAKOTA	0.049814399	0.024894	0.8726753
13	NEW MEXICO	0.025073208	0.023278	0.889391482
14	NORTH CAROLINA	0.007864357	0.023144	0.744701147
15	NEBRASKA	0.032512792	0.013787	0.909736157
16	SOUTH DAKOTA	0.040772591	0.011922	0.914582431
17	MARYLAND	-0.020236939	0.00563	0.743164063
18	OREGON	-0.000947462	0.0018	0.795211136
19	RHODE ISLAND	0.001213861	0.00103	0.669015706
20	IDAHO	-0.004400438	-0.00789	0.869222641
21	VIRGINIA	-0.020099884	-0.01236	0.743118882
22	WEST VIRGINIA	-0.003793512	-0.016	0.779188097
23	MISSOURI	0.002399281	-0.01621	0.844884872
24	WASHINGTON	-0.022082401	-0.01668	0.797766984
25	SOUTH CAROLINA	-0.014855197	-0.01732	0.773072362
26	KANSAS	-0.003233251	-0.02272	0.887353003
27	OHIO	-0.009510639	-0.0279	0.813233554
28	PENNSYLVANIA	-0.025702134	-0.02959	0.752878904
29	GEORGIA	-0.028575726	-0.03008	0.784427762
30	MINNESOTA	-0.007247688	-0.03554	0.884492934
31	TEXAS	-0.031455591	-0.03705	0.881343246
32	WISCONSIN	-0.011648318	-0.04347	0.828523934
33	IOWA	-0.024731619	-0.05686	0.869151175
34	ARKANSAS	-0.049752492	-0.05908	0.790185213
35	ILLINOIS	-0.037395038	-0.06353	0.831258595
36	OKLAHOMA	-0.037345178	-0.06379	0.847272396
37	MASSACHUSETTS	-0.074712187	-0.079	0.685233355
38	MAINE	-0.076741062	-0.08127	0.717884302
39	INDIANA	-0.054220159	-0.08855	0.805407763
40	KENTUCKY	-0.074222535	-0.0952	0.808203995
41	NEW YORK	-0.073170573	-0.09745	0.726056457
42	LOUISIANA	-0.089919895	-0.09897	0.764423132
43	MICHIGAN	-0.071322151	-0.10245	0.793337345
44	TENNESSEE	-0.081521258	-0.11306	0.780188978
45	MISSISSIPPI	-0.100566685	-0.12039	0.790456951
46	ALABAMA	-0.104531199	-0.12211	0.754764497
47	NEW HAMPSHIRE	-0.144874349	-0.14848	0.683225691
48	VERMONT	-0.197533309	-0.22725	0.723297715

Table A.3: Pairwise Correlation between SHELDUS measures and other measure

In this table, we present pairwise correlations between different measures of climate risk.

Panel D: Pairwise Correlation					
Variables	NEGPDSI	TREND	Log (Duration)	Property_damage	Crop_damage
NEGPDSI	1.000				
TREND	0.344***	1.000			
Log (Duration)	-0.059***	0.067***	1.000		
Property_damage	0.007	0.095***	0.080***	1.000	
Crop_damage	0.127***	0.128***	0.219***	0.066***	1.000

Figure A.1: Historical drought trends for different states

This figure presents the evolution of long-term climate change trends of different U.S. main-land-states over the years. Numerical numbers 1 to 48 correspond the 48 U.S. main-land states in an alphabetical order. Every point is determined from an AR(1) model: $\boldsymbol{PDSI_{s,t} = a + b * Time_s + c * PDSI_{s,t-1} + \varepsilon_{s,t}}$ using monthly frequency state-level historical PDSI data extending back to 1895.The upward (downward) trends indicates the higher (lower) exposure to climate change risk for the firms located in a certain state at a certain point of time.