University of Texas Rio Grande Valley

ScholarWorks @ UTRGV

Economics and Finance Faculty Publications
and Presentations

Robert C. Vackar College of Business &
Entrepreneurship

8-2021

The impact of climate change on the cost of bank loans

Siamak Javadi

The University of Texas Rio Grande Valley

Abdullah Al Masum

The University of Texas Rio Grande Valley

Follow this and additional works at: https://scholarworks.utrgv.edu/ef_fac

Part of the [Finance Commons](#)

Recommended Citation

Javadi, S. and Masum, A. A. (2021) 'The impact of climate change on the cost of bank loans', *Journal of Corporate Finance*, 69, p. 102019. doi: 10.1016/j.jcorpfin.2021.102019.

This Article is brought to you for free and open access by the Robert C. Vackar College of Business & Entrepreneurship at ScholarWorks @ UTRGV. It has been accepted for inclusion in Economics and Finance Faculty Publications and Presentations by an authorized administrator of ScholarWorks @ UTRGV. For more information, please contact justin.white@utrgv.edu, william.flores01@utrgv.edu.

The Impact of Climate Change on the Cost of Bank Loans

Siamak Javadi¹ siamak.javadi@utrgv.edu and **Abdullah Al Masum**^{2,*} masuma@uwosh.edu

¹Assistant professor of finance at Robert C. Vackar College of Business and Entrepreneurship, The University of Texas – Rio Grande Valley, Brownsville, TX 78520, USA;

²College of Business, Department of Finance and Business Law, the University of Wisconsin Oshkosh, Oshkosh, WI 54901, USA;

*Corresponding author.

Abstract

We find robust empirical evidence that firms in locations with higher exposure to climate change pay significantly higher spreads on their bank loans. To alleviate the concerns related to using firms' headquarters in determining climate risk exposure, we exploit the economic link between a firm and its customers and find that the exposure of a firm's customers to climate risk also adversely affects that firm's cost of borrowing. In the cross-section, we find that the long-term loans of poorly rated firms drive the effect. Overall, our evidence suggests that lenders increasingly view climate change as a relevant risk factor.

JEL Classification: G21, G32, Q54

Keywords: Climate Change; Drought; Bank Loans; Loan Spreads

“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 adverse impact of climate risk on the economy and its growth. For example, the Economist Intelligence Unit (2015) finds that the Value at Risk of manageable assets due to climate risk is \$4.2 trillion.¹ In a recent survey, Kreuger et al. (2020) document that investors are becoming increasingly concerned about the financial implications of climate risk. 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.*"² Additionally, consistent with the trend that climate change has been a top shareholder proposal issue in recent years (Painter 2020), 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 climate-related issues and will vote against management and board directors who do not.

Given that climate risk cannot be easily hedged, 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 (Cogan 2008; Chava 2014; Fard et al. 2020) and the evidence suggests that banks are becoming increasingly sensitive to environmental issues (Chang et al. 2018; Degryse et al. 2020). More than thirty leading global banks will no longer provide financing to coal-related projects or coal power firms.³ Further, bank loans are one of the most important sources of external finance (Houston and James 1996; Allen et al. 2013). More importantly, it is a well-established notion in the

¹ 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

² <https://www.npr.org/2020/01/14/796252481/worlds-largest-asset-manager-puts-climate-at-the-center-of-its-investment-strate>.

³ http://ieefa.org/wp-content/uploads/2019/02/IEEFA-Report_100-and-counting_Coal-Exit_Feb-2019.pdf

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, to the extent that investors perceive climate change as a relevant risk factor, we hypothesize that banks are likely to take climate risk into account when lending to firms located in areas more vulnerable to climate risk.

Our climate risk measure is based on Palmer Drought Severity Index (PDSI), developed by Palmer (1965). PDSI is a widely used measure in economics, finance, and climate research (Dai 2011; Hong et al. 2019; Huynh et al. 2020) that extends back to 1825 and is available for 48 states (excludes Washington D.C., Alaska, and Hawaii). Like Huynh et al. (2020), we construct our measure of climate risk by taking the average of the monthly PDSI for each state every year. We choose to focus on drought because climate risks need not be limited to carbon exposures. As noted by Hong et al. (2019), natural disasters amplified by climate change can cause significant disruption to firms' production process and impose substantial damage to their profits. Among the natural disasters that might be intensified by climate change, drought is the most devastating for economic activities (Huynh et al. 2020; Hong et al. 2019; Lesk et al. 2016).

However, it is possible that our PDSI measure could be capturing the short-term variation in weather rather than the long-term trend in climate. According to the National Aeronautics and Space Administration (NASA), "*Climate is how the atmosphere "behaves" over relatively long periods of time.*"⁴ 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. We compute this trend in droughts by following Hong et al. (2019) and estimating a trend-stationary model, an AR (1) model with a time trend, using PDSI Index time series data. This measure of climate risk, TREND, is the coefficient on the time trend. As noted by Hong et al. (2019), TREND can be

⁴ See https://www.nasa.gov/mission_pages/noaa-n/climate/climate_weather.html

interpreted as the long-term trend in drought and, thus, is arguably a more reliable measure of climate risk. Moreover, since climate change - the change in the long-term trend of climate- has a gradual nature and is, by definition, slow-moving, there is a concern that using continuous variables such as PDSI or TREND to measure climate risk may be misleading. Thus, for our third measure, we use an indicator variable approach. Every year we sort our sample loans based on the TREND exposure of the borrowing firms. The indicator variable is equal to one if a borrowing firm is in the top quartile and zero if it is in the bottom quartile. This measure directly compares the cost of borrowing of firms more exposed to climate risk to those with less exposure and is similar to the measures used in Hong et al. (2019) and Huynh et al. (2020).

Following Huynh et al. (2020), we use the state location of a firm's headquarter to determine its exposure to climate risk. Prior research shows that firms' headquarter locations are usually close to their operations and core business activities (Coval and Moskowitz 1999; Pirinsky and Wang 2006; Ivkovic and Weisbenner 2007; Hilary and Hui 2009; Chaney et al. 2012; Korniotis and Kumar 2013; Tuzel and Zhang 2017). Thus, for each loan in our sample, obtained from Loan Pricing Corporation's (LPC) DealScan database, we identify the state of the borrowing firm's headquarter and match it with our measures of climate risk. Our final sample is comprised of 32,999 unique bank loans issued to 5,243 unique US firms from 1986 to 2017.

Supporting the view that climate change is a relevant risk factor to lenders, we find a robust positive association between our measures of climate risk and loan spreads that is both statistically and economically significant. Loan spreads of firms in the top quartile of climate risk exposure are about 4.4% larger than those of firms in the bottom quartile. This finding is insensitive to the inclusion of financial and quasi-public firms. It is also robust to different model specifications, inclusion of year, industry, and loan type and purpose fixed effects as well as

different ways of clustering the standard errors. As a robustness, 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 that are associated with natural hazards linked to climate change. Regression results using these climate risk measures confirm our earlier findings.

Overall, our results are consistent with the documented adverse effect of climate change on the cost of issuing municipal bonds (Painter 2020) and add to the findings in Huynh et al. (2020) who document an increase in the forward-looking cost of equity due to drought.

Using a firm's headquarter to determine its exposure to climate risk is a legitimate concern with our analysis. A firm's headquarter location and its actual operation location might be different in some cases, which could undermine the credibility of our findings. We alleviate this concern by exploiting the well-established economic link between a firm and its customers. Prior research has documented a myriad of evidence on the economic link between a firm and its customers in different contexts, such as capital structure (Titman 1984), dividend policy (Wang 2012), and financial distress and contagion (Hertzel et al. 2008). It follows that if a firm's customers are more exposed to climate risk, given the economic link between them, the cost of bank loans 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 repeat our analysis, using the climate risk exposure of the customers. Confirming our earlier results, we find that firms whose customers are more exposed to climate risk pay significantly higher interest on their loans.

Further, climate risk has a long-term and gradual nature and thus, it is more likely to inflict damage in the long-term. Therefore, if lenders view climate change as a risk factor, its adverse

effect should be more pronounced for long-term loans. Similarly, we expect poorly rated firms to be 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 the predictions. We find that the long-term loans of poorly rated firms drive the adverse effect of climate risk. For example, loan spreads are about 5.8% higher for long-term loans of poorly rated firms in the top quartile of climate risk than those in the bottom quartile. On the other hand, this difference is insignificant when the loan is short-term, regardless of the borrower's credit rating; or when the firm has an investment level credit rating, irrespective of its loan maturity. These findings are consistent with Painter (2020) who documents that the adverse effect of sea level rise on the cost of municipal bonds is driven by long-term issues that are poorly rated.

We verify these findings by conducting a quasi-natural experiment based on an event that could significantly increase lenders' 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 to the United Kingdom government and is the largest and most widely known and discussed report related to climate change. Our difference-in-differences analysis shows that the spreads of long-term loans issued to poorly rated firms rose significantly over a 10-year window surrounding the Stern Review. However, there was no significant change in the spreads of loans issued to investment grade firms, regardless of loan maturity.

Our paper contributes to the literature on multiple fronts. First, it contributes to a fast-growing literature investigating the impact of climate risk on firms and financial markets (Chava 2014; Bernstein et al. 2019; Ginglinger and Moreau 2019; Painter 2020; to name a few). Most of

the prior studies examine the pricing of climate risk and whether it is consistent with rational asset pricing models (Bansal et al. 2016; Hong et al. 2019; Bolton and Kacperczyk 2020a) or are focused on quantifying the climate risk (Campbell and Diebold 2005; Daniel et al. 2017).

However, as noted by Huynh et al. (2020), the ultimate question to managers “*making investment decisions is whether climate change risks should be accounted for in the required rate of return.*” We answer this question by studying the effect of climate risk, as measured by drought conditions, on the cost of borrowing. We document a significant premium in the cross-section of loan spreads due to exogenous variation in drought conditions. Our main findings are consistent with Delis et al. (2020) and together with the results in Huynh et al. (2020), who examine the impact of droughts on the cost of equity, provide a more comprehensive picture of the adverse impact of climate risk on firms’ cost of capital. Thus, our findings can be of interest to academicians, managers, practitioners, and policymakers alike.

Second, our paper adds to the evidence on the financial consequences of climate change. These consequences can be in the form of physical risk (Hong et al. 2019; Painter 2020), regulatory risk (Chava 2014; Farid et al. 2020), and transition risk stemming from climate-related innovations (Delis et al. 2020; Bolton and Kacperczyk 2020b). The survey by Kreuger et al. (2020) indicates that investors believe that these risks, especially the regulatory component, have already started to be realized. Our results suggest that lenders are indeed concerned about these climate change risks and that they require a premium for bearing them.⁵

Third, our results also contribute to the literature on the pricing of long-run risky cash flows and disaster risk models. These models solve the equity risk premium puzzle of Mehra and Prescott (1985) by introducing a low-probability catastrophic risk into asset pricing models

⁵ As noted by Painter (2020), the debate about the causes of climate change has no impact on this premium. Requiring this premium is the consequence of the increase in the above risks and uncertainty about repaying loans to lenders caused by climate change, regardless of climate risk realization.

(Rietz 1988; Barro 2006 and 2015). Our results provide novel empirical evidence supporting these theories by showing that a long-run natural disaster risk measured by droughts is priced in the cross-section of loan spreads. Fourth, this study contributes to the literature on the determinants of the cost of bank loans. Our results reflect the sensitivity of banks to climate risk and add to the evidence on environmentally sensitive lending provided by Cogan (2008), Chava (2014), Chang et al. (2018), Fard et al. (2020) and Degryse et al. (2020). We show that the risks associated with climate change also affect the pricing and other non-pricing features of loans in addition to the usual default risk proxies.

This study is organized as follows. In Section 2 we review the literature and develop our main hypotheses. Section 3 discusses the data. We report our main empirical findings in Section 4 and conduct subsample analysis in Section 5. We examine lenders' attention in Section 6 and investigate the impact of climate risk on other contractual features of loans in Section 7. Section 8 concludes.

2. Literature Review and Hypothesis Development

Climate risk exposure is broadly categorized into physical risk, directly imposed by costs and damages associated with extreme weather events and natural disasters (e.g., food producers' exposure to prolonged droughts; see Hong et al. 2019); regulatory risk, originating from government policies and regulations to curb carbon emission and combat climate change (e.g., California SB 32 bill that aims at reducing greenhouse gas emissions to 40% below the 1990 levels by 2030⁶; see Fard et al. 2020 and Chava 2014); and transition risk emanating from climate-related innovations that could be disruptive to certain industries (e.g., 80% drop in the market capitalization of US coal firms over the past decade attributable to the rapid growth in the

⁶ https://leginfo.ca.gov/faces/billNavClient.xhtml?bill_id=201520160SB32

renewable energy sector.⁷ In 2019, US renewable energy consumption surpassed coal for the first time⁸; also see Delis et al. 2020; Bolton and Kacperczyk 2020b). According to the findings in Kreuger et al. (2020), the majority of investors believe that these risks, especially regulatory risks, have already begun to materialize, and 26% of them indicated that they are already incorporating climate risks into their valuation models.

The issue of how financial markets price climate risk has been the subject of a growing literature in asset pricing, and the evidence largely suggests that climate risk is priced in various financial assets and real estate. For instance, in the equity market, Bolton and Kacperczyk (2020a) find a robust carbon premium in the cross-section of U.S. stock returns. Bansal et al. (2016 and 2017) develop an asset pricing model that incorporates climate change as a long-run risk and show that the model matches not only the projected temperature path but also the observed stock market returns. Similarly, examining the effects of environmental pollution on the cross-section of stock returns, Hsu et al. (2020) develop a rational asset pricing model in which a pollution premium is obtained for high emitting firms, highlighting the economic link between environmental regulation risk and stock returns. While these results are consistent with efficient pricing of climate risk, growing evidence indicates that climate risk may be underpriced. Hong et al. (2019) show that drought conditions carry a premium in the cross-section of stock returns in an international sample, but the results are consistent with the underreaction to climate risk. Recent studies by Garvey et al. (2018) and In et al. (2019) suggest that a long-short portfolio constructed from stocks with low versus high emission intensity generates significantly positive alpha. Mispricing is also reported in studies by Daniel et al. (2017) and Kumar et al. (2019). In another related study focused on the stock markets and

⁷ <https://ieefa.org/market-cap-u-s-coal-companies-continues-fall/> and <https://ieefa.org/u-s-coal-companies-continue-to-lose-market-value/>

⁸ <https://www.eia.gov/todayinenergy/detail.php?id=43895>

predicated on the fact that the world is trying to transition away from fossil fuels to renewable energy, Bolton and Kacperczyk (2020b) document a significant premium for the carbon-transition risk in the cross-section of stock returns of more than 14,000 firms in 77 countries. However, in their other study, Bolton and Kacperczyk (2020c) exploit the exogenous shock caused by the U.K. carbon disclosure mandate in 2013 and find that carbon emissions disclosure significantly lowers the stock returns of a sample of U.K. firms.

In the real estate market, Bernstein et al. (2019) find that sea level rise reduces the value of exposed homes by about 6.6% compared to unexposed properties. On the other hand, Murfin and Spiegel (2020) find no evidence of such an effect on residential real estate prices. But the insight in the results of Baldauf et al. (2020) suggests that house prices reflect the heterogeneity in beliefs about climate risks. They find houses exposed to climate risk sell at a discount only when they are located in *believer* neighborhoods (i.e., believer in long-run climate risk). Giglio et al. (2018), however, use real estate pricing data to estimate long-run discount rates for valuing investment in climate change mitigation.

Several studies also investigate the effect of climate risk in the credit markets. Painter (2020) finds that the U.S. 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. Using a news-based measure of climate risk developed by Engle et al. (2020), Huynh and Xia (2020) show that climate risk news is priced in the cross-section of bond returns. They show that for a representative firm in their sample, cost of debt increases by \$3.6 million. Consistent with the pricing of the transition risk in the stock market documented by Bolton and Kacperczyk (2020b), Delis et al. (2020) also find evidence for the pricing of transition risk in bank loans. Their results show the transition risk that the fossil fuel reserves would become

stranded due to short- or medium-term change in regulations or public policy is priced in loan spreads after 2015 but not before. Similarly, Seltzer et al. (2020) show higher yield spreads and lower credit ratings are associated with poor environmental performance of firms, particularly for those in areas with more stringent environmental regulations. Using an international sample and focusing on the regulatory risk, Fard et al. (2020) reach a similar conclusion that firms facing more stringent environmental regulations pay higher spreads on their loans and have lower credit ratings.

At the firm level, there is evidence that extreme temperatures not only have an adverse impact on corporate earnings (Addoum et al. 2019), but also are associated with declining revenues and operating income (Pankratz et al. 2019). Gillingier and Moreau (2019) show that firms decrease their debt and adopt a more conservative leverage policy when facing greater climate risk. A similar result is documented in Elnahas et al. (2018), who find that U.S. firms in counties more prone to natural disasters maintain a lower leverage. On the other hand, Javadi et al. (2020) use a sample of firms from 41 countries and provide evidence that firms with higher exposure to climate risks increase their cash holdings. Huynh et al. (2020) find that climate risk in the form of drought is not easily diversifiable and the market prices this risk into firm-level equity risk premium. They document an increase in the forward-looking cost of equity due to drought conditions. Chava (2014) finds that investors demand a higher cost of capital for firms excluded by environmental screens. Similarly, the evidence in Degryse et al. (2020) indicates that green firms, those reporting in the Carbon Disclosure Project (CDP), pay significantly lower spreads on their loans, and that this effect is even stronger if the loan syndicate can also be classified as green.

It is clear from the above discussion that climate risk has an adverse effect on firms' cost of capital. Given the crucial role of bank loans as an important, if not the most important, source of external finance, along with the fact that banks are well-informed and sophisticated economic agents that are uniquely positioned to monitor their borrowers and assess their risks as well as their documented sensitivity with respect to climate risk, we hypothesize that banks take climate risks into account when making lending decisions:

H₁: Firms located in areas more exposed to climate risk pay higher spreads on their loans relative to firms located in areas with less climate risk exposure

As discussed above, one of the salient features of climate risk is its long-run nature (Bansal et al. 2016 and 2017). Long-run disaster risk models (Rietz 1988; Barro 2006 and 2015) also imply that climate risk is more likely to cause damage in a few decades compared to a few years. Thus, we expect the adverse effect of climate risk to be stronger for loans with longer maturities. In a similar vein, we expect this adverse effect to be more pronounced among loans issued to poorly rated firms. These firms are more financially constrained, and it is significantly harder for them to finance necessary changes to their (comparatively weaker) infrastructure and operations to mitigate the physical, regulatory, and transition risks imposed by climate change. In fact, Painter (2020) finds that the increase in the cost of issuing long-term municipal bonds resulting from sea level rise is exclusively driven by poorly rated bonds. Moreover, credit rating agencies have already begun to incorporate climate risk into their valuation models. This is evident not only in academic studies mentioned earlier (Fard et al. 2020; Seltzer et al. 2019), but more importantly, credit rating agencies such as Moody's have explicitly stated this intention and have taken actions to evaluate firms' climate risk exposure.⁹ The situation is likely to be exacerbated for

⁹ Moody's purchased 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, 761 cities, and more than 3,000 counties in the US.

poorly rated firms due to calls for more transparency and better climate risk disclosure. Ilhan et al. (2020) find that 79% of institutional investors believe climate risk disclosure is at least as important as financial disclosure. This leads to the cross-sectional implication of our main hypothesis:

H₂: The adverse effect of climate risk on the cost of bank loans is more pronounced for long-term loans and loans issued to poorly rated firms.

3. Data and Empirical Design

3.1. Loan Data

We obtain syndicated loan data from Thomson Reuters Loan Pricing Corporation, DealScan. Specifically, we study loans that originated between 1980 and 2017. Following the literature (Flannery 1994; Diamond and Rajan 2000), we exclude financial and quasi-public firms (SIC code, 6000-6999, 9000-9999). It is worth mentioning that we reconduct our entire analysis using a sample that includes financials and quasi-public firms. These results are reported in the internet appendix and are consistent with the ones reported in the paper. 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 use the all-in-spread-drawn variable (the total annual spread paid over London Interbank Offered Rate (LIBOR)) to measure the cost of bank loans. 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 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 37.4% of its assets with debt and pays a loan spread of about 177 basis points. The average loan facility has a size of about \$673 million, matures in about 48 months, and has about 8 participants in the loan syndicate. About 49% of the loans in our sample are secured, whereas term loans represent about 27% of the loans in our sample.

3.2. Measuring Climate Risk

3.2.1. PDSI data

We collect historical PDSI data from the National Climate Data Center (NCDC) of the US National Oceanic and Atmospheric Administration (NOAA) updated in monthly frequency and extends back to 1895¹⁰. This data is collected by specific measuring geo-stations from 48 different states (the dataset is not available for Alaska, and we exclude data from Hawaii so that our focus would be on the US mainland). Following Huynh et al. (2020), we aggregate the data to the 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 ($-PDSI$) as the measure of climate risk in our analysis, where higher values are associated with greater drought-like conditions. This climate risk measure has a mean value of -0.052 across all states during our sample period. The standard deviation of this measure is about 1.67, more than twice the mean (in absolute value terms), suggesting substantial variation in our climate risk measure. This measure of climate (drought) risk is similar to the one used in Huynh et al. (2020).

¹⁰ Available at www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers [Accessed on December 15, 2018]

3.2.2. Estimating TREND

While our first climate risk measure, NEGPDSI, is fairly accurate in measuring drought intensity and is widely used in climate studies (Dai 2011), there is a concern that 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.¹¹ 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:

$$PDSI_{s,t} = \alpha_s + \beta_s Time + \gamma_s PDSI_{s,t-1} + \varepsilon_{s,t} \quad (1)$$

Here, our parameter of interest is β_s , which captures the differential time trends in droughts of each state as well as the longer-run climate change vulnerability of the states to droughts. We estimate this regression for each state separately one month at a time. Specifically, we estimate β_s for state S in month m , using the PDSI data for that state going back to the earliest date available until month m . The starting point of the estimation is fixed to the earliest data available, and the rolling window expands as we move forward in time to estimate β_s in month $m+1$, $m+2$ and so on. We construct our second measure, $TREND_S$, by taking the average of the estimated monthly β_s to aggregate it to the yearly level. To remain consistent with our first measure, we multiply this measure by -1. In this way, the greater the $TREND_S$ in any given year, the larger the exposure to climate risk (long-term trend in drought) for State S in that year. This climate risk measure has a mean of -0.021 and a standard deviation of 0.060, which is almost three times larger than the mean, implying substantial variation in this measure. Moreover, the correlation

¹¹ See <https://www.climate.gov/taxonomy/term/3434>

between TREND and NEGPDSI is about 34%, which suggests that a substantial portion of the variation in TREND is unrelated to NEGPDSI, adding more credence to the argument that PDSI may be capturing variation in the weather and temporary fluctuations in the drought, rather than the long-term trend in the drought.

Table A.2 in the appendix reports average α and β in regression (1) over the entire sample period for each state, and ranks the state based on their average β exposure. California has the highest average TREND (average β) value of 0.071, while Vermont has the lowest value of -0.227. Some of the states with higher long-term drought trend are Florida, New Jersey, Montana, Connecticut, Delaware, Wyoming, Utah, Arizona, Colorado, and Nevada. Accordingly, some of the states with lower drought 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 drought trends. Figure A.1 (in the Appendix) is a graphical representation of the evolution of TREND for 48 states in mainland U.S. There are clearly substantial differences in TREND patterns among states. While some of the states show a gradual increase in TREND towards drought, few others show the opposite. Using California and Vermont as two extreme examples, Figure 1 illustrates this point.

Moreover, climate change -the change in the long-term trend of climate- is gradual, and thus, by definition, is slow-moving. Figure 1 clearly depicts the fact that TREND is slow-moving. This raises a concern that using continuous variables such as PDSI or TREND to measure climate risk may be misleading. We address this concern by using an indicator variable. Every year we sort the loans based on the borrowing firms' TREND. TREND Dummy is set to one if a borrowing firm is in the top quartile (high exposure to TREND risk) and is equal to zero if the firm is in the bottom quartile (low exposure to TREND risk). Both Hong et al. (2019) and Huynh

et al. (2020) employ similar approaches. One advantage of this approach is that the coefficient on this dummy directly compares the loan spreads between firms that are highly exposed to climate (drought) risk and those with small exposure.

Finally, we merge these climate risk measures with our Dealscan loan data based on the state location of the borrowing firms headquarters obtained from COMPUSTAT. The final dataset contains 32,999 unique bank loans issued to 5,243 unique US firms from 1986 to 2017.

3.3. Empirical Design

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

$$\begin{aligned} \text{Log (Spread)}_{i,j,s,t} = & \alpha + \beta \text{ Climate Risk}_{s,t} + \gamma \text{ Firm Controls}_{j,t} + \delta \text{ Loan Controls}_{i,t} + \\ & \text{Industry FE}_j + \text{Year FE}_t + \varepsilon_{i,j,s,t} \end{aligned} \quad (2)$$

The unit of observation is loan facility. $\text{Spread}_{i,j,s,t}$ denotes the spread on loan i , issued in year t to firm j , whose headquarter is in state S . The dependent variable, Log (Spread) , is log-transformed version of loan spread which is the all-in-drawn spread over LIBOR. The coefficient of interest is β . A positive and statistically significant β would suggest an adverse impact of climate (drought) risk on the cost of bank loans and would be consistent with our main hypothesis. 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, they may have higher borrowing costs. This leads to leverage as another firm-level control variable. Leverage is one of the main inputs in Merton's (1974) distance to default formula; thus, firms with 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. We also control for firms' profitability because profitable firms have a lower chance of default and are expected to pay lower spreads on their loans. Similarly, firms with higher market-to-book ratio have higher valuations and greater growth opportunities (Hovakimian 2006), and are, therefore, expected to have lower interests on their loans.

The second set of control variables is related to loan characteristics. These variables include 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 and industry fixed effects. As highlighted in Huynh et al. (2020), the inclusion of industry and year fixed effects represents a generalized difference-in-differences specification that aids with causal interpretation in a regression setting (Bertrand et al. 2004; Angrist and Pischke 2009; Armstrong et al. 2012). We also include bank fixed effects. In addition to controlling for differences in bank sizes that affect their volume of lending (Kroszner and Strahan 2001), bank fixed effects also control for time-invariant characteristics of the main lender that could affect loan spreads. Prior studies have shown that the time-invariant characteristics of banks have a significant impact on their lending decisions and have been used

in their model specifications (e.g., Gropp and Heider 2010; Kroszner and Strahan 2001; Goss and Roberts 2011). We use one-way clustered robust standard errors at the firm level as well as a two-way cluster at the firm and state level in separate specifications.

4. Empirical Findings

4.1. Univariate Analysis

Our first evidence on the adverse impact of climate risk on the cost of bank loans is reported in Table 2. In panel A, the correlation between loan spreads and TREND as well as NEGPDSI is positive and statistically significant. In panel B, we sort loan facilities into quartiles based on their exposure to our measures of climate risk and report the mean loan spread for each quartile. Bali et al. (2016) point out that unlike other methodologies, portfolio analysis is a nonparametric technique that does not rely on any assumptions about the functional form of the variable under investigation and is, therefore, useful for understanding the cross-sectional relations. Sorting based on NEGPDSI (TREND), we can see that the average loan spread is 172 (170.4) bps in the bottom quartile (Q1) and increases almost monotonically to 184.5 (187.3) bps in the top quartile (Q4). The difference, 12.5 (16.9) bps, is statistically significant. The main setback of this technique is the difficulty to control for a large number of variables. However, as Bali et al. (2016) argue if the pattern emerging from a portfolio analysis is monotonic or near monotonic, as is the case here, it is a strong indication that the result of the difference portfolio (Q4-Q1) is not spurious. Thus, this result suggests that loans issued to borrowers facing greater exposure to climate risk carry significantly higher interest rates.

It is noteworthy to highlight that belonging to the top or bottom quartile of climate risk is exclusively determined by the state where a firm's headquarter is located. It is unlikely and hard to argue that climate risk was a significant factor when firms chose a state for their headquarters.

Therefore, if we accept the premise that our measures of climate risk are exogenous, the significant difference in the loan spreads resulting mainly from the difference in the exogenous variation in the drought conditions of the geographical locations of firms' headquarters is a reliable indication that climate risk does have an adverse impact on the cost of bank loans.

4.2. 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 columns 1 through 6 of Panel A, we begin by running the regression using only NEGPDSI, and then sequentially add different sets of control variables to better assess the impact of NEGPDSI on loan spreads. The magnitude of the coefficients on NEGPDSI does not vary with model specifications, suggesting a robust adverse impact of climate risk on loan spreads. In columns 7 to 9, we include all control variables and sequentially add year and industry fixed effects. The coefficients on NEGPDSI continue to be positive and statistically significant. We use robust standard errors in this panel. In Panel B, we begin with a specification like that of column 9 in Panel A and then include bank fixed effects and cluster the standard errors by firm as well as state and firm. In all specifications, the coefficient on NEGPDSI is positive and statistically significant. Focusing on the last three specifications that have the richest set of fixed effects, the coefficient on NEGPDSI ($\beta=0.010$) indicates that a one standard deviation increase in NEGPDSI (1.675) is associated with about 1.68% ($100 \times 1.675 \times 0.01$) increase in loan spread.¹²

The coefficients of the control variables in all specifications have the expected sign and are 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

¹² $\left(\frac{\partial}{\partial (\text{climate risk})} \right) \ln(\text{spread}) = \alpha + \beta (\text{climate risk}) + \gamma \text{ Firm Controls} + \delta \text{ Loan Controls} + \text{Industry FE} + \text{Year FE} + \varepsilon$
 $\frac{d(\text{spread})}{\text{spread}} = d(\text{climate risk}) \times \beta \Rightarrow 100 \times \frac{d(\text{spread})}{\text{spread}} = 100 \times d(\text{climate risk})\beta \Rightarrow \% \Delta \text{spread}$

spreads. More profitable firms pay lower interest on their loan (though the effect is statistically insignificant). Firms with a high market-to-book ratio are valued more by the market and are relatively farther from financial distress. Therefore, they pay a lower loan spread.

4.3. Loan Spread and TREND

NEGPDSI may be picking up short-term variation in weather rather than climate change that could result in temporary fluctuations in drought conditions. The reason is that climate change is about the change in the long-term trend in the climate. To address this issue, we use our second measure of climate risk, TREND, in this section. Results are reported in Table 4. Similar to Table 3, in Panel A, we regress log of loan spreads on TREND alone (column 1) and then sequentially add different sets of control variables (columns 2 through 6). In the last three columns we include all the control variables, and sequentially add year and industry fixed effects. In Panel B, we include all the control variables along with industry and year fixed effects and then sequentially add bank fixed effects and use different methods to cluster the standard errors. We find a significantly robust negative association between TREND and loan spread in both panels. Focusing on the last column of Panel B, the coefficient on TREND ($\beta=0.272$; t -stat=3.26) indicates that a one standard deviation increase in TREND (0.060) is associated with about 1.63% increase in loan spread ($100 \times 0.060 \times 0.272$; please see footnote 12).

4.4. Loan Spread and TREND Dummy

Prior research has used continuous variables to proxy for climate risk (Huynh et al. 2020). However, as mentioned at the outset, using continuous variables such as TREND or PDSI for measuring climate risk may be misleading, since these variables, particularly TREND, are slow-moving. To alleviate this concern, we employ our indicator variable approach. TREND Dummy is one if a borrower is in the top quartile of TREND distribution in a given year and zero when in

the bottom quartile. Results are reported in Panel C of Table 4. Again, in all specifications, TREND Dummy is significantly positive. The coefficient on the dummy essentially compares the cost of bank loans between highly exposed firms and those with low exposure. Focusing on the last specification, the dummy coefficient is 0.044 (t-stat=2.11). This indicates that loan spreads are 4.4% larger for firms in top quartile of TREND exposure compared to those in the bottom quartile. Given the theoretical superiority of TREND and TREND Dummy to measure long-term climate (drought) risk, we report all of our results using these two variables for the rest of the analysis.

We further verify these results by conducting our analysis on a sample that includes financials and quasi-public firms. These results are reported in the internet appendix. For instance, the results reported in Tables IA.3 and IA.4 show that the adverse effect of climate risk on loan spreads is insensitive to the inclusion of these firms. Focusing on the last column in Panel C of Table IA.4, we find that loan spreads are 3.7% larger for firms in the top quartile of TREND compared to those in the bottom quartile.

4.5. Loan Spread and SHELDUS: A Robustness Check

As another robustness, we use 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 crop losses in dollar amount, etc.). We construct these measures using the (natural log of) duration, property losses, and crop losses (both in billion dollars adjusted for 2017) associated

¹³ Accessed from <https://cemhs.asu.edu/sheldus>

with natural hazards that are linked to climate change, namely hurricanes, thunderstorms, floods, tornados, and heavy rainfalls.

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

4.6. Loan Spread and Customer Climate Risk Exposure

A legitimate concern with our analysis is using a firm's headquarter location to determine its exposure to climate risk. 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, Huynh et al. (2020) find that firms have greater real estate ownership in headquarter state, suggesting a firm's headquarter location is a reasonable proxy for the location of its operation and core business activities. However, this approach has limitations. It is easy to argue that a firm's headquarter, and its main operating locations may not necessarily be the same. This issue could undermine the credibility of our findings. In this section, we exploit the well-documented 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 loans. The interlink between customers and firms is a heavily researched subject and prior findings have established this economic link in different areas such as capital structure (Titman 1984); earnings management and accounting conservatism (Hui et al. 2012); spillover effect of (adverse) shocks to customers

on firms' stock returns (Cohen and Frazzini 2008); dividend policy (Wang 2012); and financial distress and contagion (Hertzel et al. 2008).¹⁴

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.¹⁵ 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-coding¹⁶. We estimate the long-term trend in drought for the customers, TREND_CSTMR, following the procedure described in Section 3.2.2. The dummy version is also constructed the same way as before. 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, TREND_CSTMR. Employing this dataset, we use TREND_CSTMR 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 should charge higher interests on the loans issued to that firm, predicting a positive coefficient on customers' climate risk variable in model (2). Findings in Table 6 support this prediction.

¹⁴ See Kale and Meneghetti (2014) for an excellent review.

¹⁵ Accessed from <https://www.esrl.noaa.gov/psd/data/gridded/data.pdsi.html> [Accessed on June 25, 2019]

¹⁶ We use <https://www.latlong.net/Show-Latitude-Longitude.html>

Using TREND in Panel A, we document a robust positive association between the climate risk exposure of the customers and the loan spreads 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 relatively stable and insensitive to model specifications, establishing more confidence in identifying the adverse economic impact of climate risk on the cost of bank loans. We find similar results in Panel B. The coefficient on TREND_CSTMR_dummy is positive and statistically significant. Focusing on the last column in Panel B, our result suggests that firms whose customers are in the top quartile of exposure to climate (drought) risk pay about 5.7% higher spreads on their loans compared to firms whose customers are in the bottom quartile of the climate risk exposure. Given the economic link between our sample firms and their customers and that our climate risk measures are arguably exogenous, these results establish more confidence in a causal interpretation of our findings. Overall, results are consistent with our main hypothesis and indicate that climate risk, as measured by the long-term trend in drought conditions, has a significant adverse impact on firms' cost of borrowing.

4.7. Moderating Effect of Insurance

Our empirical evidence indicates that lenders view climate change as a relevant risk factor and incorporate this risk in their lending decisions. It follows that the documented adverse effect of climate risk on loan spreads should be attenuated in the presence of insurance. A widely known financial instrument that provides insurance for banks against the risks of their borrowers is credit default swaps (CDS). Credit default swaps are effectively insurance-like contracts that provide buyers protection against the credit risk of a borrower. The CDS market has rapidly become the most prominent and liquid credit derivative, encompassing approximately half of the

entire credit-derivatives market (Blanco et al. 2005). Thus, these CDS contracts are easily accessible to banks.

Early studies on the impact of CDS on firms and lending practices suggest that CDS can improve lending efficiency for high-quality borrowers (Parlour and Winton 2013) and that firms can maintain higher leverage ratios and longer debt maturities (Saretto and Tookes 2013). These findings are mainly attributed to the hedging ability that CDS offers to lenders that mitigates frictions in the supply side of credit markets. However, recent theoretical and empirical findings in the literature indicate that one of the main functions of lenders, the incentive to monitor, would be distorted and undermined when banks can buy credit protection. Initiation of CDS gives rise to the “empty creditor problem” (Bolton and Oehmke 2011), in which a bank without exposure to borrowers has reduced incentive to monitor and evaluate their risks. Empirical evidence largely supports the predictions of this theory (Ashcraft and Santos 2009; Subrahmanyam et al. 2014; Subrahmanyam et al. 2017). Therefore, to the extent that CDS provides insurance to banks against the borrowers’ risks and undermines their incentive to monitor, we expect the adverse effect of climate risk to be significantly less pronounced among firms that are referencing a trading CDS.

We investigate this issue and report supporting evidence in Table 7. We split our sample into firms with CDS and without CDS. The coefficients on TREND and TREND Dummy are significantly positive only for the subsample without CDS, indicating that banks price in the adverse effect of climate risk only when they cannot buy insurance against their borrowers’ risks. The coefficient on TREND Dummy suggests that loan spreads are 5.6% higher for non-CDS firms in the top quartile of climate exposure compared to non-CDS firms in the bottom quartile.

5. Subsample Analysis

5.1. Loan Subsample Regressions

In this section, we investigate the cross-sectional heterogeneity in the effect of climate risk on the cost of bank loans by running regressions for a series of loan subsamples. Climate risk has a long-term nature in the 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 higher spreads 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. Painter (2020) finds that the U.S. 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.

Moreover, the adverse impact of climate risk is also expected to be more pronounced for poorly rated firms. Prior research has shown that the adverse effect of climate risk is more pronounced for non-investment rated firms (Painter 2020; Fard et al. 2020; Seltzer et al. 2020). In addition, Moody's has viewed climate change as a credit risk factor as early as November 2016 and according to the global head of assessments at Moody's Investors Service, they are *"taking these risks very seriously"*.¹⁷ 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.

¹⁷ https://www.moodys.com/research/Moodys-sets-out-approach-to-assessing-the-credit-impact-of--PR_357629

We explore these cross-sectional variations and report the results in Table 8. Results in Panel A 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 ratings below that are in the non-investment group. We use TREND in Panels A1 and A2. 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. Similar results emerge from Panels A3 and A4, in which we use TREND Dummy. We find that the adverse effect of climate risk is exclusively driven by poorly rated firms. Focusing on the last specification in Panel A4, the coefficient on the TREND Dummy indicates that spreads are 5.5% larger for loans issued to poorly rated firms that are located in the top quartile of climate risk compared to those poorly rated ones in the bottom quartile.

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. Consistent with our hypothesis, we find that the adverse effect of climate risk is driven by loans with longer maturities. For instance, while there is no difference between the spreads on short-term loans issued to firms in the top and bottom quartiles of climate risk, for long-term loans this difference is 5.5% and statistically significant (Panel B3). These results are consistent with our hypothesis and demonstrate that the adverse effect of climate risk is concentrated on poorly rated firms and on long-term loans, hinting at the possibility that the effect may be driven by long-term loans issued to poorly rated firms. We investigate this conjecture in the next section.

5.2. Loan Subsample Driving the effect

In this section, we examine the conjecture that the adverse effect of climate risk is concentrated in the long-term loans issued to poorly rated firms. We first split our sample into investment and non-investment groups as well as short- and long-term loans in the same way we described in the previous section. Thus, we have a total of four loan portfolios created based on the borrowing firms' credit ratings and loan maturity. We run regression model (2) on these loan portfolios and report the results in Table 9. We use TREND in Panel A and TREND Dummy in Panel B.

Results are consistent with our conjecture in both panels. The coefficients on TREND and TREND Dummy are positive and statistically significant only for the portfolio comprised of long-term loans issued to poorly rated firms. Using the coefficient on the TREND Dummy in Panel B, we find that the cost of borrowing is 5.8% higher for long-term loans issued to poorly rated firms that are located in the top quartile of the climate risk distribution compared to long-term loans of poorly rated firms in the bottom quartile. This difference is insignificant for all other loan portfolios including, long-term loans of investment-grade firms and short-term loans of poorly rated firms.

It is known that loan spreads of poorly rated firms, like their bond yield spreads, are very sensitive. In a regression setting, where loan or yield spreads are the dependent variable, the coefficients estimated for the non-investment sample are generally larger than those for the investment subset (or the entire sample), suggesting an amplification of the effect being studied. This amplification is not always connected to an economic justification. Thus, there is a concern that our finding that the adverse effect of climate risk is driven by the loans of poorly rated firms, could be an artifact of our sample and simply a reflection of the above sensitivities. In a similar vein, there is a concern that banks are charging higher spreads on loans issued to poorly rated

firms because they are riskier. These concerns suggest that our climate risk proxies would then have to have positive significant coefficients when estimated for a sample of loans issued to poorly rated firms, regardless of loan maturity. However, the insignificant result for short-term loans issued to poorly rated firms ameliorates these concerns. Thus, as far as the climate risk is concerned, lenders do not price their loans higher for poorly rated firms if the loans are short-term. Long-term loans (and bonds) also face a similar issue. As a dependent variable in a regression, spreads on long-term loans (and bonds) could produce coefficient estimates that would imply a more pronounced effect. Similarly, finding insignificant coefficients for the subsample of long-term loans issued to investment-grade firms alleviates the concern related to the sensitivity of the spreads of long-term loans. Moreover, throughout the analysis so far, the magnitude of the effect (based on TREND Dummy) has been fairly stable at around 5.5%, adding more credibility to our argument that the effect is driven by long-term loans of poorly rated firms.

5.3. Food Industry Subsample

As discussed by Hong et al (2019), drought conditions have a considerable negative impact on the 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 severe drought conditions. Given that our measures of climate risk are based on drought, it follows that the effect of climate risk should be stronger among the borrowing firms in the food industry. However, we find no significant difference between firms in the “Food” industry and others.¹⁸ While this insignificant result could be the artifact of our sample since there are only about 1,000 loan observations that belong to the Food

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.

industry, it is more likely that the result reflects the fact that lenders do not simply see much difference between firms in the Food industry and others. A similar insignificant result is documented in Bolton and Kacperczyk (2020b). They find carbon premium is not significantly different in countries that have been exposed to greater damages caused by climate disasters such as droughts and floods. Thus, as highlighted by Bolton and Kacperczyk (2020b), this finding suggests that the documented drought premium may not necessarily reflect the physical risk component of climate risk. Alternatively, this finding can be viewed as consistent with the financial market underreaction to climate risk documented by Hong et al. (2019).

6. Stern Review

In this section, we examine the role of investor attention in pricing of the climate risk in 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 an 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 to the United Kingdom government and is the largest and most widely known and discussed report related to climate change and is commonly credited with substantially raising awareness about climate change.

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 loans after the Stern Review would suggest that lenders' attention significantly affects the pricing of climate risk in the loan spreads. We run a difference-in-differences analysis

surrounding the release of the Stern Report and report the results in Table 10. We use TREND in Panel A and TREND Dummy in Panel B. Focusing on the first column in Panel B, we find that the interaction term between the TREND Dummy and Stern is statistically insignificant. This finding suggests that loan spreads did not significantly change subsequent to the release of the report, implying that lenders' attention did not affect the pricing of the climate risk in loan spreads. Inclusion of the financials does not alter this result (column 2).

This result is inconsistent with our expectation and the findings in Painter (2020). However, we provided evidence that climate risk is mainly concentrated in a subsample of loans that are long-term and issued to poorly rated firms. Therefore, it is 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 separately for these two groups. In addition to using the entire sample period, to better isolate the effect of market reaction, we run our analysis on a sample that is restricted to a 10-year window surrounding the release of the Stern Report.

Focusing on Panel B and the investment group (the four columns in the middle), we find no significant difference between the long-term loans (LM) issued to investment-grade firms before and after Stern. The three-way interaction term between the TREND Dummy, LM, and Stern is insignificant. This finding does not change when we restrict the sample to a 10-year period surrounding the Stern or if we include financial firms. Results are virtually the same in Panel A. In contrast, the results for the poorly rated firms (last four columns) suggest that spreads on their long-term loans rose significantly after the Stern release when we restrict our sample to a 10-year period surrounding the release of the Stern Report. The three-way interaction is significantly positive in Panel B ($\beta=0.141$; $t\text{-stat}=2.15$). Inclusion of the financials strengthens this result.

Results in Panel A, however, are significantly weaker. The three-way interaction is only significant when we include financials and restrict the sample to the 10-year window. This result is consistent with our earlier findings that the adverse effect of climate is driven by long-term loans of poorly rated and highlights the significant cross-sectional heterogeneity in the effect of climate risk on the cost of bank loans. Figure 2 depicts that subsequent to the release of the Stern Report in 2006, loan spreads increased substantially for long-term loans of poorly rated firms that are in the top quartile of climate risk (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 (not reported). Overall, these results provide suggestive evidence on the gradual increase in the attention of lenders to climate risk, and they are consistent with the documented underreaction of the financial market to climate risk by Hong et al. (2019).¹⁹

7. Other Loan Contractual Features

Our results up to this point provide evidence that lenders view climate change as a risk factor and therefore charge higher spreads 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 their loans, increase up-front fees, and include more restrictive covenant in their loan

¹⁹ Degryse et al. (2020) find that green firms borrow at a significantly lower spread, especially when the lender consortium can also be classified as “green”. In contrast to our Stern results here, they show that their result is significant and large only after the Paris Agreement in December 2015, indicating that lenders pay close attention to policy events that affect environmental attitudes. However, we have to note that the Stern report was released about a decade before Paris Climate Accord, and during this period the attitude and the attention of the public, investors, and the governments to issues related to the environment and climate had shifted drastically.

contracts. In this section, we focus on these contractual features of loans and test these predictions.

We separately investigate the effect of climate risk on contractual features of loans by estimating an augmented version of regression model (2) that uses each feature as the dependent variable. We report the results in Table 11. TREND is used in Panel A and TREND Dummy in Panel B. Overall, results are consistent with our prediction and indicate that an increase in the climate risk exposure of a borrower is associated with a significant shortening of the loan maturity, a decrease in the number of participants in the loan syndicate, and an increase in upfront fees, the number of covenants included in the loan, and the likelihood of issuing a secured loan. Focusing on Panel B, we find that banks shorten the maturity of their loans by about 2.2%, increase their upfront fees by 10.5%, and are 3.1% more likely to issue secured loans when a borrowing firm is exposed to climate risk compared to the one that is not. For the average firm in our sample that has 3.49 covenants included in its loan, high exposure to climate risk is associated with about 4.5% ($0.156/3.49=4.47\%$) increase in the number of covenants written on its loan. Further, the size of the loan syndicate is also about 9% smaller for exposed firms. This result signifies the fact that lenders do view climate change as a risk factor and is consistent with the arguments in Chava (2014) and Bolton and Kacperczyk (2020c) that investors apply exclusionary filters based on climate risk. 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 a narrower lender base and would have to pay higher spreads on its loans.

8. Concluding Remarks

We provide empirical evidence supporting that climate change is viewed as a risk factor by lenders and is priced in the loan spreads they charge as well as in other contractual features of their loans. Exploiting 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 as well. Subsample analyses show that the effect of climate risk is driven by the long-term loans of poorly rated firms. The analysis around the release of the Stern Report also shows a significant increase in the loan spreads of long-term loans of poorly rated firms, but not for other loans. Further, we find no climate (drought) risk premium for short-term loans or loans issued to investment-rated firms as well as those issued to firms referencing a trading CDS. These loans are, therefore, susceptible to a negative shock in their values due to different dimensions of climate risks, namely physical, regulatory, and transition risks, that could potentially lead to substantial losses to investors and could spread to other sectors of the economy and undermine the stability of the financial system (Carney 2015). Our results, thus, add supporting evidence to the documented underpricing of climate risk in the literature.

The underpricing of climate risk is mainly due to inadequate disclosure requirement that prevents the markets from understanding this risk. While general information on the negative impact of climate risk on the economy is not in short supply, many investors believe the current generic language used in the limited climate risk disclosure of firms is uninformative, insufficient, and imprecise for investors, regulators, and policymakers to assess this risk. In fact, 79% of surveyed investors believe that climate risk reporting is at least as important as financial reporting and that climate risk reporting should be mandatory and standardized, very much like financial reporting (Ilhan et al. 2020). While climate risk disclosure entails a cost-benefit tradeoff, the described sentiment by the market participants suggests that the investors' view is

that the benefits outweigh the costs. This observation is consistent with the theoretical predictions in Goldstein and Yang (2017) and Christensen et al. (2019) and the empirical evidence in Bolton and Kacperczyk (2020c) that shows climate disclosure reduces cost of capital and stock return volatility.

While just over 12% of listed companies globally disclose their carbon emission (Bolton and Kacperczyk 2020c), there is a growing trend by companies to release a “corporate responsibility report”. In its 2017 survey, KPMG states that “for the first time in the history of its survey, more than 60% of companies across all industry sectors” release such a report.²⁰ Beginning from 2020, BlackRock requires from the firms it invests in to release additional disclosure of climate-related risks and their plans to comply with the guidelines of the Paris Climate Accord. The U.K. has had mandatory carbon disclosure since 2013 and more countries around the world are passing regulations for mandatory climate risk disclosure. Moreover, a large number of banks, accounting for approximately 80% of the total lending volume globally, has a stated agenda to consider environmental issues when making lending decisions, limit or end funding to coal-related projects, and make finance more accessible to firms and projects involving green and renewable energy. Improved climate risk disclosure requirement not only helps banks better identify this risk among their borrowers, but more importantly, it can help the market participants better incorporate climate risk in their investment decision, leading to more efficient pricing of this risk in the financial markets. Our study highlights the necessity for enhanced and more transparent climate disclosure requirements.

Acknowledgements

²⁰ <https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2017/10/kpmg-survey-of-corporate-responsibility-reporting-2017.pdf>

We thank Binay Adhikari, Ahmed Elnahas, Incheol Kim, Mahdi Rastad, Nam Nguyen, Vladimir Atanasov, Bernard Black, Danmo Lin, Mohsen Mollagholamali, Maria Teresa Punzi (discussant), Adam Usman (discussant), Bart Lambrecht (editor), Gianfranco Gianfrate (guest editor) and two anonymous referees and other seminar participants at the University of Texas Rio Grande Valley, the 2019 Northwestern-Duke Causal Inference workshop, the 2019 Finance of Climate Change at EDHEC Business School in Paris, France, and the 2020 Financial Management Association meeting for their helpful and insightful comments. All remaining errors are ours.

Appendices

Table A.1: Variable Definitions

Variable	Definition	Source
Climate Change Proxies		
NEGPDSI	Negative Palmer Drought Severity Index (PDSI); $NEGPDSI = -1 \times PDSI$	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 AR(1) model extends back to 1895 for each state at each point of sample period using monthly frequency data; $TREND = -b \times 1,000$	AR (1) Model: $PDSI_{s,t} = \alpha_s + \beta_s \text{Time} + \gamma_s PDSI_{s,t-1} + \varepsilon_{s,t}$
TREND Dummy	= 1, if observation belongs to the top quartile (top 25%) TREND group of a year = 0, if observation belongs to the bottom quartile (bottom 25%) TREND group of a year	
TREND_CSTM	TREND determined from firms' customer segmentation locations (countries)	
TREND_CSTM Dummy	equals to 1 if TREND_CSTM is in the top quartile (top 25%) in a particular year, and equals to 0 if TREND_CSTM is in the bottom quartile (bottom 25%) in a particular year	
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
Property Damage	Property loss (in \$B) due to climate exposure (Adjusted for 2017) - aggregated to state level	SHELDUS
Crop Damage	Crop loss (in \$B) due to climate exposure (Adjusted for 2017) - aggregated to state level	SHELDUS
Loan Features		
Log (Spread)	Log of allindrawn which is the interest amount paid by borrowers annually over	LPC DealScan; $\log(\text{allindrawn})$

Log (Deal Amount)	LIBOR in basis points; Total Deal Amount; log-transformed	LPC DealScan; $\log(dealamount)$
Log (Lenders)	Number of Lenders in loan syndication; log-transformed	LPC DealScan;
Log (Maturity)	Maturity of loan in months; log-transformed	LPC DealScan;
Total Covenants	Total number of Financial and General Covenants in loan contracts	LPC DealScan;
Log (Upfront Fee)	Upfront fee paid by borrowers for loans; log-transformed	LPC DealScan; $\log(\frac{uprfee_{min} + uprfee_{max}}{2})$
Secured Loan	Dummy (=1, if the loan is secured, = 0 otherwise)	LPC DealScan
Firm Characteristics		
Log (Asset)	Total Asset; log-transformed	COMPUSTAT; $\log(at)$
LEV Ratio	Total debt over Asset	COMPUSTAT; $\log(\frac{dlc+dlt}{at})$
MTB	Market to Book value	COMPUSTAT; $(prcc_f \times csho + lt)/(ceq + lt)$
ROA	Return on Assets	COMPUSTAT; ib/at
Loan Type and Purpose Dummies		
TERMLOAN	Loan type dummy (= 1, if the type of borrowing is a term loan, = 0 otherwise)	LPC DealScan
REVOLVER	Loan type dummy (= 1, if the type of borrowing is a revolving credit line, = 0 otherwise)	LPC DealScan
MERGER	Loan purpose dummy (= 1, if the purpose of borrowing is to spend in merger activities, = 0 otherwise)	LPC DealScan
LBO	Loan purpose dummy (= 1, if the purpose of borrowing is to spend in leveraged buyout, = 0 otherwise)	LPC DealScan
CORPPURP	Loan purpose dummy (= 1, if the purpose of borrowing is expenditure in general corporate purposes, = 0 otherwise)	LPC DealScan
DEBTPAY	Loan purpose dummy (= 1, if the purpose of borrowing is debt repayment, = 0 otherwise)	LPC DealScan
WORKCAP	Loan purpose dummy (= 1, if the purpose of borrowing is to raise working capital, = 0 otherwise)	LPC DealScan
OTHERTYPE	Loan type dummy (= 1, if the type of borrowing is neither a revolving credit line nor a term loan, = 0 otherwise)	LPC DealScan
Others		
Stern	Dummy (=1, if year is later than 2006, = 0 otherwise)	
LM (Long Maturity)	Dummy (=1, if loan maturity is above the sample median; =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.1: AR(1) model summary

This table presents the summary of our AR(1) model: $PDSI_{s,t} = \alpha_s + \beta_s Time + \gamma_s PDSI_{s,t-1} + \varepsilon_{s,t}$. 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 in the year 1986 and vice-versa. This ranking is subject to change based on the time-beta of each state at different time points in our study.

RANK	STATE	α_s	β_s	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	-0.0078	0.869222641
21	VIRGINIA	-0.020099884	-0.01226	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	-0.009510637	-0.0279	0.813233554
28	PENNSYLVANIA	-0.025702134	-0.02959	0.752878904
29	GEORGIA	-0.025575726	-0.03008	0.784427762
30	MINNESOTA	-0.007206688	-0.03554	0.884492934
31	TEXAS	-0.031455501	-0.03705	0.881343246
32	WISCONSIN	-0.011648318	-0.04347	0.828523934
33	IOWA	-0.0124731619	-0.05686	0.869151175
34	ARKANSAS	-0.041752492	-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 Climate Risk Measures

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

Panel D: Pairwise Correlation

Variables	NEGPDSI	TREND	Log (Duration)	Property Damage	Corp 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	

Corp 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: $PDSI_{s,t} = \alpha_s + \beta_s Time + \gamma_s PDSI_{s,t-1} + \varepsilon_{s,t}$ 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.

Supplementary data
Supplementary material

References

- Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, 33(3), 1331-1366.
- 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.
- Angrist, J. D., & Pischke, J. S. (2009). Instrumental variables in action: sometimes you get what you need. *Mostly harmless econometrics: an empiricist's companion*, 113-220.

- Armstrong, C. S., Balakrishnan, K., & Cohen, D. (2012). Corporate governance and the information environment: Evidence from state antitakeover laws. *Journal of Accounting and Economics*, 53(1-2), 185-204.
- Ashcraft, A. B., & Santos, J. A. (2009). Has the CDS market lowered the cost of corporate debt?. *Journal of Monetary Economics*, 56(4), 514-523.
- Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33(3), 1256-1295.
- Bali, T., Engle, R. & Murray, S. (2016), Empirical Asset Pricing: The Cross Section of Stock Returns. Wiley ISBN: 978-1-118-09504-1
- Bansal, R., Kiku, D., & Ochoa, M. (2016). *Price of long-run temperature shifts in capital markets* (No. w22529). National Bureau of Economic Research.
- Bansal, R., Ochoa, M., & Kiku, D. (2017). *Climate change and growth risks* (No. w23009). National Bureau of Economic Research.
- Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics*, 121(3), 823-866.
- Barro, R. J. (2015). Environmental protection, rare disasters and discount rates. *Economica*, 82(325), 1-23.
- 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.
- Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly Journal of Economics*, 119(1), 249-275.
- Blanco, R., Brennan, S., & Marsh, I. W. (2005). An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *The journal of Finance*, 60(5), 2255-2281.
- Bolton, P., & Kacperczyk, M. (2020a). *Do investors care about carbon risk?* *Journal of Financial Economics*, Forthcoming
- Bolton, P., & Kacperczyk, M. T. (2020b). Global Pricing of Carbon-Transition Risk. *Available at SSRN 3550233*.
- Bolton, P., & Kacperczyk, M. T. (2020c). Signaling through Carbon Disclosure. *Available at SSRN 3755613*.
- Bolton, P., & Oehmke, M. (2011). Credit default swaps and the empty creditor problem. *The Review of Financial Studies*, 24(8), 2617-2655.
- Bradley, M., & Roberts, M. R. (2015). The structure and pricing of corporate debt covenants. *The Quarterly Journal of Finance*, 5(02), 1550001.
- Campbell, S. D., & Diebold, F. X. (2005). Weather forecasting for weather derivatives. *Journal of the American Statistical Association*, 100(469), 6-16.
- Carney, M. (2015). Breaking the Tragedy of the Horizon—climate change and financial stability. *Speech given at Lloyd's of London*, 29, 220-230.
- 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.

- Christensen, H. B., Hail, L., & Leuz, C. (2019). Economic analysis of widespread adoption of CSR and sustainability reporting standards. *Available at SSRN 3315673*.
- 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.
- Daniel, K. D., Litterman, R. B., & Wagner, G. (2017). *Applying asset pricing theory to calibrate the price of climate risk* (No. w22795). National Bureau of Economic Research.
- Davis, J. C., & Henderson, J. V. (2008). The agglomeration of headquarters. *Regional Science and Urban Economics*, 38(5), 445-460.
- Degryse, H., Goncharenko, R., Theunisz, C., & Vadazs, T. (2020). When green meets green. *Available at SSRN 3724237*.
- Delis, M. D., de Greiff, K., and Ongena, S. (2020). Being Stranded with Fossil Fuel Reserves? Climate Policy Risk and the Pricing of Bank Loans. *Available on SSRN. 3125017*.
- 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.
- Diamond, D. W., & Rajan, R. G. (2000). A theory of bank capital. *The Journal of Finance*, 55(6), 2431-2465.
- Elnahas, A., Kim, D., & Kim, I. (2018). Natural disaster risk and corporate leverage. *Available at SSRN 3123468*.
- Engle, R. F., Giglio, S., Kelly, B., Lee, C., & Stroebe, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.
- Fard, A., Javadi, S., & Kim, I. (2020). Environmental regulation and the cost of bank loans: International evidence. *Journal of Financial Stability*, 51, 100797.
- Flannery, M. J. (1994). Debt maturity and the deadweight cost of leverage: Optimally financing banking firms. *The American economic review*, 84(1), 320-331.
- Garvey G.T., Iyer, M., Nash, J. (2018). Carbon foot print and productivity: Does the “E” in ESG capture efficiency as well as environment? *Journal of Investment Management* 16(1), 59-69.
- Giglio, S., Maggiori, M., Stroebe, J., & Weber, A. (2018). *Cost-Benefit Evaluation of Investments in Climate Change Abatement*. Working paper.
- Ginglinger, E., & Moreau, Q. (2019). Climate risk and capital structure. *Université Paris-Dauphine Research Paper*, (3327185).
- Goldstein, I., & Yang, L. (2017). Information disclosure in financial markets. *Annual Review of Financial Economics*, 9, 101-125.
- Graham, J. R., Li, S., & Qiu, J. (2008). Corporate misreporting and bank loan contracting. *Journal of Financial Economics*, 89(1), 44-61.
- Gropp, R., & Heider, F. (2010). The determinants of bank capital structure. *Review of finance*, 14(4), 587-622.
- 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.
- Hertzel, M. G., Li, Z., Officer, M. S., & Rodgers, K. J. (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics*, 87(2), 374-387.
- 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.
- Hovakimian, A. (2006). Are observed capital structures determined by equity market timing?. *Journal of Financial and Quantitative analysis*, 221-243.
- Hsu, Po-Hsuan, Kai Li, and Chi-Yang Tsou. "The pollution premium." *Available at SSRN 3578215* (2020).
- Hui, K. W., Klasa, S., & Yeung, P. E. (2012). Corporate suppliers and customers and accounting conservatism. *Journal of Accounting and Economics*, 53(1-2), 115-135.
- Huynh, T. D., Nguyen, T. H., & Truong, C. (2020). Climate risk: The price of drought. *Journal of Corporate Finance*, 65, 101750.
- Huynh, T., & Xia, Y. (2020). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, forthcoming.
- Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2020). Climate risk disclosure and institutional investors. *Swiss Finance Institute Research Paper*, (19-66).
- In, S. Y., Park, K. Y., & Monk, A. (2017). Is 'being green' rewarded in the market? an empirical investigation of decarbonization risk and stock returns. *International Association for Energy Economics (Singapore Issue)*, 16, 43.
- Ivković, Z., & Weisbenner, S. (2007). Information diffusion effects in individual investors' common stock purchases: Do they follow their neighbors' investment choices. *The Review of Financial Studies*, 20(4), 1327-1357.
- Javadi, S., Masum, A. A., Molagholamali, M., & Rao, R. P. (2020). Climate Change and Corporate Cash Holdings: Global Evidence. *Available at SSRN 3717092*.
- Korniotis, G. M., & Kumar, A. (2013). State-level business cycles and local return predictability. *The Journal of Finance*, 68(3), 1037-1096.
- Kroszner, R. S., & Strahan, P. E. (2001). Bankers on boards:: monitoring, conflicts of interest, and lender liability. *Journal of financial Economics*, 62(3), 415-452.
- Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), 1067-1111.
- Kumar, A., Xin, W., & Zhang, C. (2019). Climate sensitivity and predictable returns. *Available at SSRN 3331872*.
- Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84-87.
- Mehra, R., & Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of monetary Economics*, 15(2), 145-161.

- 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.
- Murfin, J., & Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate?. *The Review of Financial Studies*, 33(3), 1217-1255.
- 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.
- Pankratz, N., Bauer, R., & Derwall, J. (2019). Climate change, firm performance, and investor surprises. Available at SSRN 3443146.
- Parlour, C. A., & Winton, A. (2013). Laying off credit risk: Loan sales versus credit default swaps. *Journal of Financial Economics*, 107(1), 25-45.
- 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.
- Rietz, T. A. (1988). The equity risk premium a solution. *Journal of monetary Economics*, 22(1), 117-131.
- Saretto, A., & Tookes, H. E. (2013). Corporate leverage, debt maturity, and credit supply: The role of credit default swaps. *The Review of Financial Studies*, 26(5), 1190-1247.
- Seltzer, L., Starks, L. T., & Zhu, Q. (2020). Climate regulatory risks and corporate bonds. Available at SSRN 3563271.
- Stern, N. (2008). The economics of climate change. *American Economic Review*, 98(2), 1-37.
- Subrahmanyam, M.G., D.Y. Tang, and S.Q. Wang. (2014). "Does the Tail Wag the Dog? The Effect of Credit Default Swaps on Credit Risk." *Review of Financial Studies*, 27, 2926-60.
- Subrahmanyam, M.G., D.Y. Tang, and S.Q. Wang. (2017). "Credit default swaps, exacting creditors and corporate liquidity management." *Journal of Financial Economics*, 124 (2), 395-414.
- Titman, S. (1984). The effect of capital structure on a firm's liquidation decision. *Journal of financial economics*, 13(1), 137-151.
- Tuzel, S., & Zhang, M. L. (2017). Local risk, local factors, and asset prices. *The Journal of Finance*, 72(1), 325-370.
- Wang, J. (2012). Do firms' relationships with principal customers/suppliers affect shareholders' income?. *Journal of Corporate Finance*, 18(4), 860-878.

Table 2: Summary statistics

This table reports summary statistics of different variables from our main dataset constructed based on a cross-section of 32,999 different loan facilities (data source: LPC DealScan) issued to 5,243 unique firms headquartered in 48 U.S. mainland-states during the years 1986 to 2017 excluding the financial and quasi-public firms (2-digit SIC codes: 60-69, and 90-99). Table A.1 (appears in Appendices) provides detailed descriptions and sources of all variables.

VARIABLE	N	MEAN	SD	P10	P25	P50	P75	P90
Climate Change Proxies								
NEGPDSI	32,999	-0.052	1.675	-2.222	-1.148	-0.138	0.950	2.101
TREND	32,999	-0.021	0.060	-0.097	-0.061	-0.030	0.029	0.063

Log (Duration)	32,999	2.354	1.280	0.693	1.386	2.303	3.401	3.434
Crop Damage (\$B, 2017 Adjusted)	32,999	0.211	0.721	0	0	0.003	0.054	0.635
Property Damage (\$B, 2017 Adjusted)	32,999	0.960	5.061	0.008	0.032	0.102	0.407	1.537
Loan Features								
Spread (basis points)	32,999	177.268	124.124	40	87.5	150	250	325
Maturity (months)	32,999	47.558	22.980	12	35	58	60	72
Deal Amount (\$M)	32,999	673	1470	29	83	250	700	1600
Lenders	32,984	8.437	8.728	1	2	6	11	19
Total Covenants	32,999	3.490	3.547	0	0	3	6	9
Log (Upfront fee)	6,608	3.457	1.061	2.189	2.708	3.401	4.248	4.605
Secured Loan	32,999	0.493	0.500	0	0	1	1	1
Firm Characteristics								
Log (Asset)	32,999	7.030	1.901	4.574	5.682	7.001	8.324	9.562
LEV Ratio	32,999	0.374	0.231	0.080	0.208	0.351	0.516	0.705
MTB	32,946	1.698	1.154	0.973	1.128	1.400	1.894	2.683
ROA	32,981	0.034	0.389	-0.053	0.008	0.042	0.080	0.127
Loan Type and Purpose Dummies								
TERMLOAN	32,999	0.272	0.445	0	0	0	1	1
REVOLVER	32,999	0.628	0.83	0	0	1	1	1
MERGER	32,999	0.141	0.348	0	0	0	0	1
LBO	32,999	0.003	0.091	0	0	0	0	0
CORPPURP	32,999	0.401	0.490	0	0	0	1	1
DEBTPAY	32,999	0.153	0.365	0	0	0	0	1
WORKCAP	32,999	0.172	0.377	0	0	0	0	1
OTHERTYPE	32,999	0.122	0.328	0	0	0	0	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	0.343***	1.000				
Spread	0.078***	0.048***	1.000			
Panel B: Loan Portfolios						
Basis	Q1	Q2	Q3	Q4	Difference (Q4-Q1)	t-stats
NEGPDSI	171.923	175.571	178.531	184.461	12.538***	6.466
TREND	170.393	178.894	173.102	187.276	16.883***	8.932

Table 3: Loan Spreads and PDSI

This table presents Log of Spread as a function of Negative Palmer Drought Severity Index (NEGPDSI) and controls. In columns (1) to (9) of Panel A, we show how the relationship evolves with the addition of different sets of controls, and fixed effects with robust standard errors. In Columns (1), (2), and (3) of Panel B, we consider Year fixed effect and Industry (two-digits SIC) fixed effect. There 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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEGPDSI	0.041*** (16.29)	0.042*** (17.89)	0.043*** (18.21)	0.040*** (17.98)	0.046*** (20.26)	0.045*** (20.76)	0.043*** (20.40)	0.014*** (6.84)	0.010*** (5.17)
Log (Asset)					- 0.146*** (-62.35)	- 0.127*** (-54.62)	-0.130*** (-54.81)	-0.185*** (-72.25)	-0.187*** (-70.01)
LEV Ratio					0.688*** (37.63)	0.524*** (28.71)	0.529*** (29.94)	0.588*** (35.25)	0.554*** (33.60)
MTB					- 0.091*** (-6.70)	- 0.083*** (-6.39)	-0.078*** (-6.12)	-0.082*** (-6.07)	-0.079*** (-5.70)
ROA					-0.075 (-0.84)	-0.073 (-0.86)	-0.070 (-0.83)	-0.063 (-0.82)	-0.056 (-0.76)
TERMLOAN		0.845*** (54.20)		- 0.227*** (-8.83)		0.620*** (11.51)	0.382*** (-16.43)	-0.047** (-2.24)	-0.067*** (-3.28)
REVOLVER		0.421*** (28.70)		- 0.721*** (-27.67)		0.241*** (17.09)	-0.835*** (-34.86)	-0.417*** (-19.37)	-0.432*** (-20.25)
MERGER		0.154*** (13.65)		0.425*** (24.43)		0.023** (2.11)	0.234*** (14.36)	0.173*** (11.78)	0.179*** (12.27)
LBO			0.670*** (21.41)	0.830*** (24.35)			0.815*** (21.49)	0.958*** (25.06)	0.975*** (24.92)
CORPPURP			-0.011 (-0.99)	0.302*** (19.31)			0.298*** (21.00)	0.086*** (6.42)	0.081*** (6.17)
DEBTPAY			-0.016 (-1.17)	0.089*** (16.28)			0.100*** (6.01)	0.207*** (13.38)	0.200*** (13.09)
OTHERTYPE			- 0.772*** (-51.77)	- 1.255*** (-41.65)			-1.210*** (-43.78)	-0.689*** (-26.83)	-0.691*** (-27.24)
WORKCAP			0.005*** (1.49)	0.414*** (24.69)			0.290*** (18.72)	0.151*** (10.49)	0.143*** (10.12)
Constant	4.914*** (1,128.30)	4.398*** (318.35)	5.001*** (542.47)	5.277*** (176.11)	5.842*** (177.85)	5.425*** (145.91)	6.316*** (141.31)	6.371*** (144.94)	6.408*** (149.04)
Obs.	32,999	32,999	32,999	32,999	32,928	32,928	32,928	32,928	32,927
Adj-R ²	0.007	0.133	0.117	0.210	0.182	0.252	0.320	0.489	0.504
Year FE	No	No	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	No	No	No	Yes
Bank (lending) FE	No	No	No	No	No	No	No	No	No
State Clustering	No	No	No	No	No	No	No	No	No
Firm Clustering	No	No	No	No	No	No	No	No	No

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
NEGPDSI	0.010*** (5.17)	0.010*** (3.52)	0.010*** (8.92)	0.010*** (4.76)	0.010*** (3.38)	0.010*** (7.82)
Log (Asset)	-0.187*** (-70.01)	-0.187*** (-22.13)	-0.187*** (-17.83)	-0.180*** (-56.37)	-0.180*** (-17.74)	-0.180*** (-13.36)
LEV Ratio	0.554*** (33.60)	0.554*** (17.84)	0.554*** (24.97)	0.507*** (30.71)	0.507*** (16.96)	0.507*** (22.33)
MTB	-0.079*** (-5.70)	-0.079*** (-4.72)	-0.079*** (-40.54)	-0.084*** (-5.72)	-0.084*** (-4.96)	-0.084*** (-54.49)
ROA	-0.056	-0.056	-0.056	-0.037	-0.037	-0.037

	(-0.76)	(-0.76)	(-0.53)	(-0.64)	(-0.64)	(-0.45)
TERMLOAN	-0.067***	-0.067***	-0.067***	-0.061***	-0.061**	-0.061***
	(-3.28)	(-2.71)	(-12.66)	(-2.88)	(-2.53)	(-15.53)
REVOLVER	-0.432***	-0.432***	-0.432***	-0.380***	-0.380***	-0.380***
	(-20.25)	(-16.50)	(-77.88)	(-17.24)	(-14.83)	(-61.65)
MERGER	0.179***	0.179***	0.179***	0.177***	0.177***	0.177***
	(12.27)	(8.51)	(37.70)	(12.19)	(8.78)	(32.45)
LBO	0.975***	0.975***	0.975***	0.835***	0.835***	0.835***
	(24.92)	(15.49)	(21.78)	(21.87)	(14.05)	(14.96)
CORPPURP	0.081***	0.081***	0.081***	0.099***	0.099***	0.099***
	(6.17)	(4.41)	(26.07)	(7.64)	(5.45)	(22.43)
DEBTPAY	0.200***	0.200***	0.200***	0.192***	0.192***	0.192***
	(13.09)	(9.61)	(64.78)	(12.69)	(9.40)	(48.01)
OTHERTYPE	-0.691***	-0.691***	-0.691***	-0.631***	-0.631***	-0.631***
	(-27.24)	(-20.91)	(-34.01)	(-24.28)	(-19.07)	(-27.93)
WORKCAP	0.143***	0.143***	0.143***	0.151***	0.151***	0.151***
	(10.12)	(6.93)	(26.36)	(10.62)	(7.60)	(33.65)
Constant	6.408***	6.408***	6.408***	6.341***	6.340***	6.340***
	(149.04)	(88.34)	(104.75)	(155.21)	(78.08)	(80.70)
Obs.	32,927	32,927	32,927	31,886	31,886	31,886
Adj-R ²	0.504	0.504	0.504	0.553	0.553	0.553
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 Spreads and TREND

This table presents Log of Spread as a function of log-growth in climate change trend (TREND) and controls. In columns (1) to (9) of Panel A, we show how the relationship evolves with the addition of different sets of controls, and fixed effects with robust standard errors. In Columns (1), (2), and (3) of Panel B, we consider Year fixed effect and Industry (two-digits SIC) fixed effect. There 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. In Panel C, we repeat the analyses of Panel B using TREND Dummy (equals to 1 if TREND is above 75% in a particular year, and equals to 0 if TREND is below 25% in a particular year) as the key independent variable instead of TREND. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TREND	0.702*** (9.90)	0.622*** (9.36)	0.614*** (9.15)	0.588*** (9.28)	0.651*** (9.99)	0.581*** (9.29)	0.514*** (8.67)	0.434*** (8.54)	0.355*** (6.92)
Log (Asset)					- 0.144*** (-61.39)	- 0.124*** (-53.70)	-0.128*** (-53.88)	-0.185*** (-72.21)	-0.187*** (-70.03)
LEV Ratio					0.694*** (37.70)	0.530*** (28.82)	0.535*** (30.11)	0.591*** (35.44)	0.555*** (33.71)
MTB					- 0.093*** (-6.78)	- 0.084*** (-6.47)	-0.079*** (-6.20)	-0.082*** (-6.12)	-0.079*** (-5.73)
ROA					-0.074 (-0.82)	-0.073 (-0.84)	-0.070 (-0.82)	-0.062 (-0.81)	-0.055 (-0.75)
TERMLOAN		0.841*** (53.89)		- 0.229*** (-9.00)		0.627*** (41.32)	-0.382*** (-16.55)	-0.046** (-2.20)	-0.067*** (-3.29)
REVOLVER		0.414***		-		0.236***	-0.838***	-0.416***	-0.431***

			0.727***						
		(28.19)	(-28.09)	(16.72)	(-35.20)	(-19.29)	(-20.24)		
MERGER		0.152***	0.424***	0.021*	0.233***	0.175***	0.180***		
		(13.39)	(24.33)	(1.87)	(14.24)	(11.87)	(12.35)		
LBO		0.675***	0.833***		0.818***	0.960***	0.977***		
		(21.63)	(24.49)		(21.92)	(25.20)	(25.00)		
CORPPURP		-0.008	0.305***		0.301***	0.086***	0.081***		
		(-0.71)	(19.48)		(21.15)	(6.43)	(6.16)		
DEBTPAY		-0.020	0.285***		0.097***	0.209***	0.201***		
		(-1.43)	(16.04)		(5.81)	(13.51)	(13.19)		
OTHERTYPE		-	-		-1.207***	-0.688***	-0.690***		
		0.765***	1.254***						
		(-50.98)	(-41.78)		(-43.84)	(-26.77)	(-27.23)		
WORKCAP		0.059***	0.417***		0.295***	0.151***	0.143***		
		(4.69)	(24.83)		(19.01)	(10.53)	(10.15)		
Constant	4.927***	4.415***	5.009***	5.291***	5.837***	5.424***	5.312***	6.374***	6.412***
	(1,078.36)	(317.65)	(535.49)	(177.28)	(176.90)	(141.05)	(140.67)	(145.25)	(149.49)
Obs.	32,999	32,999	32,999	32,999	32,928	32,928	32,927	32,927	32,927
Adj-R ²	0.003	0.132	0.110	0.205	0.175	0.241	0.313	0.505	0.505
Year FE	No	No	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	No	No	No	Yes
Bank (lending) FE	No	No	No	No	No	No	No	No	No
State Clustering	No	No	No	No	No	No	No	No	No
Firm Clustering	No	No	No	No	No	No	No	No	No

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
TREND	0.355***	0.355***	0.355***	0.272***	0.272**	0.272***
	(6.92)	(3.09)	(4.74)	(5.18)	(2.30)	(3.26)
Log (Asset)	-0.187***	-0.187***	-0.187***	-0.180***	-0.180***	-0.180***
	(-70.03)	(-22.27)	(-18.00)	(-56.33)	(-17.76)	(-13.42)
LEV Ratio	0.555***	0.555***	0.555***	0.508***	0.508***	0.508***
	(33.71)	(17.96)	(25.67)	(30.77)	(17.03)	(22.84)
MTB	-0.079***	-0.079***	-0.079***	-0.084***	-0.084***	-0.084***
	(-5.73)	(-4.76)	(-40.28)	(-5.73)	(-4.99)	(-54.25)
ROA	-0.055***	-0.055***	-0.055***	-0.037***	-0.037***	-0.037***
	(-0.75)	(-0.75)	(-0.53)	(-0.63)	(-0.63)	(-0.44)
TERMLOAN	-0.067***	-0.067***	-0.067***	-0.062***	-0.062***	-0.062***
	(-3.25)	(-2.71)	(-12.69)	(-2.91)	(-2.55)	(-15.62)
REVOLVER	-0.31***	-0.431***	-0.431***	-0.380***	-0.380***	-0.380***
	(-20.24)	(-16.44)	(-79.42)	(-17.25)	(-14.83)	(-62.40)
MERGER	0.180***	0.180***	0.180***	0.178***	0.178***	0.178***
	(12.35)	(8.56)	(37.93)	(12.25)	(8.82)	(32.97)
LBO	0.977***	0.977***	0.977***	0.837***	0.837***	0.837***
	(25.00)	(15.55)	(22.43)	(21.97)	(14.12)	(15.32)
CORPPURP	0.081***	0.081***	0.081***	0.099***	0.099***	0.099***
	(6.16)	(4.40)	(25.91)	(7.64)	(5.45)	(22.11)
DEBTPAY	0.201***	0.201***	0.201***	0.193***	0.193***	0.193***
	(13.19)	(9.66)	(63.04)	(12.76)	(9.44)	(49.86)
OTHERTYPE	-0.690***	-0.690***	-0.690***	-0.631***	-0.631***	-0.631***
	(-27.23)	(-20.90)	(-34.83)	(-24.29)	(-19.11)	(-28.36)
WORKCAP	0.143***	0.143***	0.143***	0.151***	0.151***	0.151***
	(10.15)	(6.95)	(26.70)	(10.91)	(7.61)	(33.89)
Constant	6.412***	6.412***	6.412***	6.344***	6.344***	6.344***
	(149.49)	(89.02)	(108.21)	(135.63)	(78.71)	(82.71)
Obs.	32,927	32,927	32,927	31,886	31,886	31,886

Adj-R ²	0.505	0.505	0.505	0.553	0.553	0.553
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

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
TREND Dummy	0.054*** (5.82)	0.054*** (2.59)	0.054*** (2.85)	0.044*** (4.44)	0.044*** (1.99)	0.044*** (2.11)
Log (Asset)	-0.177*** (-45.84)	-0.177*** (-13.28)	-0.177*** (-17.09)	-0.165*** (-34.53)	-0.165*** (-10.04)	-0.165*** (-10.73)
LEV Ratio	0.563*** (24.98)	0.563*** (13.11)	0.563*** (14.22)	0.542*** (23.51)	0.542*** (13.13)	0.542*** (14.06)
MTB	-0.056*** (-3.65)	-0.056*** (-3.03)	-0.056*** (-1.81)	-0.060*** (-3.67)	-0.060*** (-3.29)	-0.060*** (-2.00)
ROA	-0.015 (-0.38)	-0.015 (-0.38)	-0.015 (-0.54)	-0.004 (-0.14)	-0.004 (-0.14)	-0.004 (-0.19)
TERMLOAN	-0.066** (-2.24)	-0.066* (-1.93)	-0.066** (-2.42)	0.067** (-2.11)	-0.067* (-1.93)	-0.067*** (-2.75)
REVOLVER	-0.412*** (-13.59)	-0.412*** (-11.45)	-0.412*** (-13.97)	-0.367*** (-11.32)	-0.367*** (-9.90)	-0.367*** (-14.56)
MERGER	0.239*** (11.31)	0.239*** (7.63)	0.239*** (9.26)	0.220*** (10.16)	0.220*** (7.14)	0.220*** (8.39)
LBO	0.952*** (17.91)	0.952*** (11.57)	0.952*** (19.30)	0.871*** (16.04)	0.871*** (10.36)	0.871*** (15.89)
CORPPURP	0.119*** (6.21)	0.119*** (4.35)	0.119*** (5.88)	0.128*** (6.56)	0.128*** (4.71)	0.128*** (6.63)
DEBTPAY	0.208*** (9.29)	0.208*** (6.73)	0.208*** (12.21)	0.192*** (8.37)	0.192*** (6.20)	0.192*** (10.52)
OTHERTYPE	-0.675*** (-18.45)	-0.675*** (-11.97)	-0.675*** (-13.85)	-0.630*** (-16.26)	-0.630*** (-12.50)	-0.630*** (-12.96)
WORKCAP	0.164*** (8.11)	0.164*** (5.45)	0.164*** (5.07)	0.172*** (8.43)	0.172*** (5.89)	0.172*** (6.07)
Constant	6.246*** (109.19)	6.246*** (59.71)	6.246*** (57.27)	6.154*** (95.06)	6.154*** (50.50)	6.154*** (41.01)
Obs.	15,325	15,891	15,891	15,325	15,325	15,325
Adj-R ²	0.512	0.512	0.512	0.557	0.557	0.557
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 Spreads 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 SHEL DUS 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. Columns (1), (2), and (3) consider 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.

Panel A: Spread and Duration (Days)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log (Duration)	0.014*** (5.27)	0.014*** (3.09)	0.014*** (7.55)	0.011*** (4.14)	0.011** (2.45)	0.011*** (4.53)
Constant	6.375*** (146.84)	6.375*** (85.28)	6.375*** (97.69)	6.314*** (133.25)	6.314*** (75.01)	6.314*** (74.99)
Obs.	32,927	32,927	32,927	31,886	31,886	31,886
Adj-R ²	0.504	0.504	0.504	0.553	0.553	0.553
Panel B: Spread and Property Damage, \$B (2017 Adjusted)						
Property Damage	0.003*** (4.51)	0.003*** (3.51)	0.003*** (18.75)	0.002*** (3.64)	0.002*** (3.00)	0.002*** (11.10)
Constant	6.405*** (148.82)	6.405*** (88.21)	6.405*** (104.44)	6.338*** (134.86)	6.338*** (77.88)	6.338*** (80.44)
Obs.	32,927	32,927	32,927	31,886	31,886	31,886
Adj-R ²	0.504	0.504	0.504	0.553	0.553	0.553
Panel C: Spread and Crop Damage, \$B (2017 Adjusted)						
Crop Damage	0.018*** (3.94)	0.018*** (2.66)	0.018*** (21.33)	0.016*** (3.45)	0.016*** (2.38)	0.016*** (14.77)
Constant	6.403*** (148.67)	6.403*** (88.16)	6.403*** (104.51)	6.335*** (134.79)	6.335*** (77.81)	6.335*** (80.50)
Obs.	32,927	32,927	32,927	31,886	31,886	31,886
Adj-R ²	0.504	0.504	0.504	0.553	0.553	0.553
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 Type & Purpose 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 6: Loan Spreads and Customer climate risk exposure

This table presents Log of Spread as a function of long-term climate change trend at customer locations (TREND_CSTMTR) and controls. Here, the customer locations are determined by matching borrower firms with Compustat Capital IQ Customer Segmentation database. The customer locations are country-level and our climate change proxy for country-level locations are available until 2014 only. As one firm can have customers at several different locations, we have repetitive observations in those cases for this part of analyses. In Panel A, we report the results with TREND_CSTMTR, and in Panel B, we use TREND_CSTMTR Dummy (equals to 1 if TREND_CSTMTR is above 75% in a particular year, and equals to 0 if TREND_CSTMTR is below 25% in a particular year). In both cases, columns (1), (2), and (3) consider 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.

Panel A: TREND						
	(1)	(2)	(3)	(4)	(5)	(6)
TREND_CSTMTR	0.299*** (6.76)	0.299* (1.80)	0.299* (1.95)	0.286*** (6.19)	0.286 (1.62)	0.286* (1.76)
Log (Asset)	-0.194***	-0.194***	-0.194***	-0.186***	-0.186***	-0.186***

	(-84.94)	(-14.21)	(-15.02)	(-67.40)	(-11.40)	(-11.97)
LEV Ratio	0.610 *** (43.31)	0.610 *** (11.90)	0.610 *** (10.63)	0.555 *** (38.85)	0.555 *** (11.01)	0.555 *** (10.06)
MTB	-0.057 *** (-5.41)	-0.057 *** (-3.02)	-0.057 *** (-3.66)	-0.060 *** (-5.64)	-0.060 *** (-3.33)	-0.060 *** (-3.95)
ROA	-0.845 *** (-11.25)	-0.845 *** (-5.76)	-0.845 *** (-6.71)	-0.784 *** (-10.18)	-0.784 *** (-5.18)	-0.784 *** (-5.96)
TERMLOAN	-0.074 *** (-4.19)	-0.074 *** (-2.12)	-0.074 *** (-2.33)	-0.085 *** (-4.62)	-0.085 *** (-2.41)	-0.085 *** (-2.50)
REVOLVER	-0.473 *** (-25.67)	-0.473 *** (-12.76)	-0.473 *** (-12.66)	-0.444 *** (-23.18)	-0.444 *** (-11.64)	-0.444 *** (-10.73)
MERGER	0.172 *** (14.79)	0.172 *** (5.17)	0.172 *** (4.16)	0.179 *** (15.53)	0.179 *** (5.72)	0.179 *** (4.78)
LBO	1.065 *** (27.96)	1.065 *** (9.44)	1.065 *** (10.58)	0.955 *** (25.90)	0.955 *** (8.56)	0.955 *** (8.87)
CORPPURP	0.077 *** (7.55)	0.077 *** (2.83)	0.077 *** (2.71)	0.092 *** (9.14)	0.092 *** (3.40)	0.092 *** (3.10)
DEBTPAY	0.185 *** (15.76)	0.185 *** (6.08)	0.185 *** (5.36)	0.163 *** (14.45)	0.168 *** (5.55)	0.168 *** (4.24)
OTHERTYPE	-0.744 *** (-35.28)	-0.744 *** (-15.54)	-0.744 *** (-15.07)	-0.709 *** (-32.45)	-0.709 *** (-14.17)	-0.709 *** (-13.02)
WORKCAP	0.165 *** (14.19)	0.165 *** (4.94)	0.165 *** (4.43)	0.175 *** (15.36)	0.175 *** (5.23)	0.175 *** (5.73)
Constant	6.401 *** (189.56)	6.401 *** (58.62)	6.401 *** (63.28)	6.347 *** (174.34)	6.347 *** (51.10)	6.347 *** (54.23)
Obs.	51,152	51,152	51,152	49,606	49,606	49,606
Adj-R ²	0.546	0.546	0.546	0.600	0.600	0.600
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

Panel B: TREND Dummy

	(1)	(2)	(3)	(4)	(5)	(6)
TREND_CSTMR_dummy	0.047 *** (6.15)	0.047 *** (1.59)	0.047 *** (1.75)	0.057 *** (6.81)	0.057 *** (1.80)	0.057 *** (1.91)
Log (Asset)	-0.177 *** (-54.64)	-0.177 *** (-8.77)	-0.177 *** (-9.04)	-0.166 *** (-41.70)	-0.166 *** (-6.97)	-0.166 *** (-7.26)
LEV Ratio	0.607 *** (31.24)	0.607 *** (9.01)	0.607 *** (9.44)	0.608 *** (30.17)	0.608 *** (9.34)	0.608 *** (9.65)
MTB	-0.039 *** (-3.50)	-0.039 *** (-1.97)	-0.039 *** (-2.39)	-0.042 *** (-3.75)	-0.042 *** (-2.25)	-0.042 *** (-2.68)
ROA	-0.756 *** (-8.02)	-0.756 *** (-3.99)	-0.756 *** (-4.52)	-0.627 *** (-6.95)	-0.627 *** (-3.47)	-0.627 *** (-3.85)
TERMLOAN	-0.079 *** (-3.05)	-0.079 *** (-1.70)	-0.079 *** (-1.72)	-0.098 *** (-3.52)	-0.098 *** (-1.90)	-0.098 *** (-1.97)
REVOLVER	-0.471 *** (-17.65)	-0.471 *** (-9.38)	-0.471 *** (-8.46)	-0.452 *** (-15.70)	-0.452 *** (-7.82)	-0.452 *** (-7.15)
MERGER	0.251 *** (14.80)	0.251 *** (5.19)	0.251 *** (4.98)	0.243 *** (13.87)	0.243 *** (5.32)	0.243 *** (5.07)
LBO	1.102 *** (23.37)	1.102 *** (8.27)	1.102 *** (8.94)	1.037 *** (21.31)	1.037 *** (7.97)	1.037 *** (7.68)
CORPPURP	0.128 ***	0.128 ***	0.128 ***	0.143 ***	0.143 ***	0.143 ***

	(8.68)	(3.21)	(3.25)	(9.48)	(3.82)	(3.97)
DEBTPAY	0.177***	0.177***	0.177***	0.170***	0.170***	0.170***
	(10.28)	(3.82)	(3.61)	(9.57)	(3.78)	(3.53)
OTHERTYPE	-0.754***	-0.754***	-0.754***	-0.722***	-0.722***	-0.722***
	(-24.55)	(-11.38)	(-9.52)	(-22.05)	(-9.66)	(-8.74)
WORKCAP	0.181***	0.181***	0.181***	0.191***	0.191***	0.191***
	(10.94)	(4.05)	(4.61)	(11.39)	(4.67)	(5.34)
Constant	6.215***	6.215***	6.215***	6.115***	6.115***	6.115***
	(140.19)	(41.41)	(43.23)	(124.14)	(36.37)	(38.24)
Obs.	25,954	25,954	25,954	25,091	25,091	25,091
Adj-R ²	0.556	0.556	0.556	0.605	0.605	0.605
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: Moderating Effect of Insurance

This table presents the moderating effect of insurance. Here we separate our sample into two groups based on the condition whether the borrower firm was insured through the Credit Default Swap (CDS) during the issuance of a loan to it. The sample is limited due to our limited availability of CDS data. The dependent variable is log (spread). Each of the models use Year fixed effect, Industry fixed effect, and Bank (Lending) fixed effect. The standard errors are two-way clustered by Firm and State. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

	With CDS	Without CDS	With CDS	Without CDS
TREND	-0.047	0.306***		
	(-0.13)	(2.73)		
TREND Dummy			0.015	0.056***
			(0.31)	(4.23)
Log (Asset)	-0.162***	-0.133***	-0.150***	-0.115***
	(-6.61)	(-9.52)	(-4.61)	(-5.55)
LEV Ratio	0.739***	0.497***	0.837***	0.517***
	(9.57)	(9.54)	(7.22)	(8.68)
MTB	-0.225**	-0.099***	-0.241***	-0.100***
	(-9.72)	(-11.73)	(-7.10)	(-10.46)
ROA	2.455***	-0.621***	-1.990***	-0.412***
	(7.29)	(-5.50)	(-5.21)	(-3.19)
TERMLOAN	0.251	0.088*	0.547	0.156**
	(0.70)	(2.10)	(1.61)	(2.48)
REVOLVER	-0.128	-0.165***	0.177	-0.071
	(-0.37)	(-3.43)	(0.52)	(-1.09)
MERGER	0.325***	0.079**	0.436***	0.113**
	(5.13)	(2.10)	(4.06)	(2.14)
LBO	0.915***	0.594***	0.949***	0.558***
	(8.23)	(6.11)	(6.44)	(4.46)
CORPPURP	0.301***	0.004	0.395***	0.066
	(7.91)	(0.14)	(7.66)	(1.59)
DEBTPAY	0.453***	0.110	0.554***	0.108**
	(5.88)	(3.20)	(6.85)	(2.12)
OTHERTYPE	-0.356	-0.423***	-0.051	-0.285***
	(-1.01)	(-7.31)	(-0.15)	(-3.15)
WORKCAP	0.308***	0.021	0.357***	0.070*
	(6.70)	(0.70)	(6.46)	(1.98)

Constant	6.193*** (14.97)	6.219*** (46.43)	5.635*** (13.02)	5.937*** (32.61)
Obs.	3,838	10,428	1,671	5,061
Adj-R ²	0.675	0.497	0.675	0.497
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank (lending) FE	Yes	Yes	Yes	Yes
State Clustering	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes

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 (or TREND Dummy) and controls (as of Table 4). Panel A1 (A3) and A2 (A4) present comparison between Investment Grade vs. Noninvestment Grade subsample, Panel B1 (B3) and B2 (B4) present comparison between Long Maturity (T3 and T4) vs. Short Maturity (T1 and T2) subsample. Models (1), (2), and (3) consider Year fixed effect and Industry (two-digits SIC) fixed effect. In model (1) we use robust standard errors, in model (2) we cluster standard errors by firm, in model (3) we use two-way clustering of standard errors by Firm and State, and in models (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: Investment vs. Noninvestment												
Panel A1: Investment and TREND							Panel A2: Noninvestment and TREND					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
TREND	0.030	0.030	0.030	0.018	0.018	0.018	0.440*	0.440*	0.440*	0.368*	0.368*	0.368*
	(0.22)	(0.10)	(0.10)	(0.13)	(0.06)	(0.06)	(8.61)	(4.41)	(4.05)	(7.06)	(3.65)	(4.59)
CONSTANT	6.115*	6.115*	6.115*	6.014*	6.014*	6.014*	6.163*	6.163*	6.163*	6.129*	6.129*	6.129*
	**	**	**	**	**	**	**	**	**	**	**	**
	(64.65)	(38.76)	(41.33)	(60.31)	(57.01)	(36.28)	(147.09)	(93.39)	(70.82)	(134.30)	(83.78)	(56.84)
Obs.	5,976	5,976	5,976	5,779	5,779	5,779	26,948	26,948	26,948	26,034	26,034	26,034
Adj-R ²	0.549	0.549	0.549	0.586	0.586	0.586	0.383	0.383	0.383	0.450	0.450	0.450
Panel A3: Investment and TREND Dummy							Panel A4: Noninvestment and TREND Dummy					
TREND Dummy	0.017	0.017	0.017	0.035	0.035	0.035	0.064*	0.064*	0.064*	0.055*	0.055*	0.055*
	(0.74)	(0.35)	(0.42)	(1.38)	(0.68)	(0.75)	(6.84)	(3.51)	(4.91)	(5.63)	(2.92)	(4.39)
CONSTANT	5.912*	5.912*	5.912*	5.701*	5.701*	5.701*	6.060*	6.060*	6.060*	6.001*	6.001*	6.001*
	**	**	**	**	**	**	**	**	**	**	**	**
	(40.15)	(27.60)	(38.40)	(34.44)	(23.84)	(24.12)	(109.76)	(63.95)	(59.76)	(96.19)	(54.68)	(45.64)
Obs.	2,564	2,564	2,564	2,443	2,443	2,443	13,324	13,324	13,324	12,815	12,815	12,815
Adj-R ²	0.573	0.573	0.573	0.616	0.616	0.616	0.385	0.385	0.385	0.450	0.450	0.450
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes

State Clustering	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Panel B: Long Maturity vs. Short Maturity												
Panel B1: Long Maturity and TREND							Panel B2: Short Maturity and TREND					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
TREND	0.381 ^{**}	0.381 ^{**}	0.381 ^{**}	0.294 [*]	0.294 [*]	0.294 [*]	0.211 ^{**}	0.211	0.211	0.098	0.098	0.098
	(5.84)	(2.94)	(3.51)	(4.47)	(2.25)	(2.38)	(2.70)	(1.59)	(1.29)	(1.17)	(0.69)	(0.62)
CONSTANT	6.323 ^{**}	6.323 ^{**}	6.323 ^{**}	6.264 [*]	6.264 [*]	6.264 [*]	6.224 ^{**}	6.224 ^{**}	6.224 ^{**}	6.212 [*]	6.212 [*]	6.212 [*]
	(128.34)	(61.67)	(45.11)	(120.59)	(52.46)	(35.66)	(71.06)	(62.08)	(63.73)	(69.98)	(64.04)	(56.51)
Obs.	17,360	17,360	17,360	16,839	16,839	16,839	15,564	15,564	15,564	14,899	14,899	14,899
Adj-R ²	0.526	0.526	0.526	0.582	0.582	0.582	0.529	0.529	0.529	0.568	0.568	0.568

Panel B3: Long Maturity and TREND Dummy							Panel B4: Short Maturity and TREND Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
TREND Dummy	0.063 ^{**}	0.063 ^{**}	0.063 ^{**}	0.055 [*]	0.055 [*]	0.055 [*]	0.022	0.022	0.022	0.004	0.004	0.004
	(5.19)	(2.72)	(4.31)	(4.39)	(2.35)	(2.30)	(1.58)	(0.93)	(0.84)	(0.29)	(0.17)	(0.16)
CONSTANT	6.090 ^{**}	6.090 ^{**}	6.090 ^{**}	5.976 [*]	5.976 [*]	5.976 [*]	6.052 ^{**}	6.052 ^{**}	6.052 ^{**}	6.063 [*]	6.063 [*]	6.063 [*]
	(90.69)	(40.90)	(38.81)	(81.63)	(34.47)	(28.63)	(48.66)	(43.58)	(70.68)	(50.74)	(46.57)	(50.80)
Obs.	8,489	8,489	8,489	8,197	8,197	8,197	7,399	7,399	7,399	7,007	7,007	7,007
Adj-R ²	0.523	0.523	0.523	0.572	0.572	0.572	0.546	0.546	0.546	0.582	0.582	0.582
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
State Clustering	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Firm Clustering	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Table 9: Loan Subsample Driving the effect

In this table, we present analyses of subsample that are (most likely) driving the effect. Here we first split our sample into Investment and Non-investment rated firms. Then, within each of the groups, we further split them into long vs. short maturities. Panel A, and Panel B present the results using TREND, and TREND Dummy as key independent variables, respectively. The dependent variable is log (spread). Each of the models use Year fixed effect, Industry fixed effect, and Bank (Lending) fixed effect. The standard errors are two-way clustered by Firm and State. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Panel A: TREND				
	Non-Investment		Investment	
	Long Maturity	Short Maturity	Long Maturity	Short Maturity
TREND	0.392*** (4.52)	0.156 (1.46)	-0.030 (-0.10)	0.037 (0.10)
CONSTANT	6.029*** (40.24)	5.937*** (55.25)	6.150*** (35.78)	6.026*** (25.87)
Obs.	14,207	11,677	2,588	3,147
Adj-R ²	0.503	0.449	0.641	0.560
Panel B: TREND Dummy				
TREND Dummy	0.058*** (3.96)	0.026 (1.23)	0.066 (1.68)	0.013 (0.21)
CONSTANT	5.855*** (33.90)	5.784*** (52.10)	5.775*** (21.25)	5.343*** (13.64)
Obs.	7,088	5,603	1,063	1,343
Adj-R ²	0.498	0.458	0.082	0.587
Other Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank (lending) FE	Yes	Yes	Yes	Yes
State Clustering	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes

Table 10: Stern Review

This table presents Difference-in-Differences (DiD) results of log (spread) around Stern Review (2006). It takes TREND – in Panel A (or TREND Dummy – in Panel B) interacted with Stern Dummy (equals 1 if a loan was issued later than the year 2006; 0 otherwise), and Long Maturity (LM) Dummy as key independent variable within different sample conditions. A 10-year window uses sample between the years 2002–2011. Each of the models use Year fixed effect, Industry fixed effect, and Bank (Lending) fixed effect. The standard errors are two-way clustered by Firm and State. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Panel A: TREND										
	Different Samples		Investment				Non-Investment			
	Without Financial	With Financial	Without Financial	With Financial	10-yr window Without Financial	10-yr window With Financial	Without Financial	With Financial	10-yr window Without Financial	10-yr window With Financial
TREND*LM*Stern			-0.560	-0.737*	-0.706	-0.676	0.022	0.186	0.428	0.748**
			(-1.34)	(-1.82)	(-1.20)	(-1.56)	(0.11)	(0.96)	(1.07)	(2.50)
TREND*Stern	-0.361*	-0.367	-0.231	-0.103	-0.443	-0.353	-0.384	-0.492*	-0.400	-
	(-1.93)	(-1.40)	(-0.44)	(-0.28)	(-0.80)	(-0.93)	(-1.64)	(-1.80)	(-1.37)	(-2.03)
LM*Stern			-0.021	0.018	-0.044	-0.000	0.033**	0.028*	0.038	0.038*
			(-0.53)	(0.51)	(-0.70)	(-0.01)	(2.13)	(1.99)	(1.34)	(1.78)
TREND*LM			0.189	-0.002	0.268	0.051	0.278**	0.108	0.183	-0.339*
			(0.70)	(-0.01)	(0.52)	(0.12)	(2.19)	(0.70)	(1.04)	(-1.82)
LM			-	-	-0.083	-	-	-	-	-
			0.069**	0.086***		0.115**	0.114***	0.108***	0.143**	0.138**
						*			*	*

[illegible]

Panel B: TREND Dummy

[illegible]

Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank (lending) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Other contractual features of loans

This table presents different contractual features of bank loans other than the Spread as a function of long-term climate change trend (TREND) – in Panel A (or TREND Dummy – in Panel B), and controls. These loan features include Deal Amount, Maturity, Number of Lenders in a Loan Syndicate, Total Covenants, Upfront Fee, and Secured Loan Dummy. Each of the models use Year fixed effect, Industry fixed effect, and Bank (Lending) fixed effect. The standard errors are two-way clustered by Firm and State. Values of t-statistics are in parentheses. ***, **, and * represent significance at 1% level, 5% level, and 10% level respectively.

Panel A: TREND						
	Log(Deal Amount)	Log(Maturity)	Log(Lenders)	Total Covenants	Log (Upfront fee)	Secured Loan
TREND	-0.417 (-1.24)	-0.188*** (-2.89)	-0.538* (-1.83)	0.311 (0.77)	0.702*** (3.32)	0.123 (1.27)
CONSTANT	14.775*** (115.39)	3.142*** (73.95)	-0.724*** (-8.48)	4.942*** (13.55)	4.505*** (28.27)	1.190*** (18.84)
Obs.	31,886	31,885	31,886	31,886	6,144	31,886
Adj-R ²	0.746	0.495	0.452	0.361	0.328	0.320
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Clustering						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Clustering						
Panel B: TREND Dummy						
	Log (Deal Amount)	Log (Maturity)	Log (Lenders)	Total Covenants	Log (Upfront fee)	Secured Loan
TREND Dummy	-0.051 (-0.86)	-0.022** (-2.36)	-0.089** (-2.04)	0.156* (1.91)	0.105*** (2.89)	0.031** (2.16)
CONSTANT	14.927*** (71.93)	3.181*** (55.78)	-0.589*** (-4.62)	4.382*** (17.36)	4.125*** (22.03)	1.074*** (15.84)
Obs.	15,325	15,325	15,325	15,325	3,022	15,325
Adj-R ²	0.763	0.501	0.476	0.370	0.339	0.328
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Clustering						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Clustering						

Figure 1: Historical Trends of Droughts (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: $PDSI_{s,t} = \alpha_s + \beta_s Time + \gamma_s PDSI_{s,t-1} + \varepsilon_{s,t}$ 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 Spreads following the Stern Review (2006)

This figure presents the difference in the loan spreads following the Stern Review (2006). Group 1 (solid line) depicts the average loan spread of the long-term loans of poorly rated firms that are in the top quartile of climate risk and group zero (dashed line) represents the average spreads of all other loans.

Highlights

- Firms in locations with higher exposure to climate risk, as measured by drought conditions, pay significantly higher spreads on their bank loans.
- Exposure of a firm's customers to climate risk increases that firm's cost of borrowing
- The adverse effect is driven by the long-term loans of poorly rated firms.
- Other non-pricing contractual features of loans are also affected