The rising tide lifts some interest rates: climate change, natural disasters, and loan pricing*

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Abstract

We investigate how corporate borrowing costs are affected by natural disasters related to climate change. We construct granular measures of borrowers' exposure to, and therefore risk associated with, various natural disasters. We then disentangle the direct effects of disasters from the effects of lenders updating their beliefs about the severity and frequency of future disasters. Following a climate change–related disaster, interest rate spreads on loans of at-risk, yet unaffected borrowers, spike both in the primary and secondary markets. These effects are amplified when attention to climate change is high and are consistent with banks' internal assessments of higher probabilities of default for these borrowers. Importantly, there is no such effect from disasters that are not aggravated by climate change. Borrowers with the most extreme exposure to climate change and those with the least ability to absorb adverse shocks suffer the highest increase in spreads.

JEL Classifications: G21, Q51, Q54

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1 Introduction

Climate change can have potentially devastating long-term economic effects (Stern, 2007), with the majority of the consequences of climate change expected towards the end of the century (Hong, Karolyi, and Scheinkman, 2020). However, the long delay before these effects fully impact the global economy can discourage actions to mitigate climate change-related risks, and the relevance of these risks from today's perspective depends heavily on discount rates (Nordhaus, 2010). As a result, large parts of the literature on climate change and financial markets have concentrated on long-lived assets such as real estate or equities (Giglio, Maggiori, and Stroebel, 2015; Murfin and Spiegel, 2020; Baldauf, Garlappi, and Yannelis, 2020), with an emphasis on estimating discount rates to capture long-run damages (Giglio, Maggiori, Rao, Stroebel, and Weber, 2018). Our paper investigates a novel channel by which climate change already shapes economic risks today, that is, through the increased frequency and severity of certain extreme weather events. With regulators and central banks increasingly worried about potential systemic risks from climate change, it is crucial to answer whether loan market participants and banks are aware of and price climate change risk.

A key challenge in linking climate change to corporate debt funding is that the average loan maturity is less than five years, while most climate change-related physical risks are projected to peak towards the end of the 21st century. Consistent with this mismatch between the maturity of financial instruments and the long horizon of climate change, Addoum, Ng, and Ortiz-Bobea (2020) find no current effect of extreme temperatures on firms, and investors have only very recently started to price projected long-term sea level rises in generally longer dated municipal bonds (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2019).

Our approach to address this issue is to focus on severe weather events (e.g., hurricanes, wildfires, and floods), which, as the substantial evidence in the Intergovernmental Panel on Climate Change (IPCC) reports indicate (Masson-Delmotte, Zhai, Pirani, Connors, Péan, Berger, Caud, Chen, Goldfarb, Gomis, Huang, Leitzell, Lonnoy, Matthews, Maycock, Waterfield, Yelekçi, Yu, and Zhou, 2021), are already intensifying in severity and frequency because of climate change.[1] These disasters are likely the first channel through which physical risks associated with climate change directly affects borrowers; therefore, these natural disasters comprise a perfect laboratory to overcome the long-term horizon challenge of climate change (Giglio et al., 2018). Importantly, these types of climate risks are already being priced by some investors, as almost two-thirds of institutional investors surveyed by Krueger, Sautner, and Starks (2020) report that they expect the physical risks of climate change to affect their credit portfolios today or within two years. Beyond the impact of climate change on loan pricing, we also assess whether extreme weather events already affect firms' financial decisions such as investments and cash holdings. This analysis provides early evidence on the consequences of climate change dynamics on corporate actions.

The most straightforward approach to assess the effect of these climate change-related natural disasters on firms' borrowing costs is to analyze the loan spreads charged by banks after borrowers are directly hit by disasters. While this approach yields evidence on financial institutions' pricing of disaster risk, it suffers from the weakness described in Nordhaus (2010) that it cannot disentangle the direct effect of the disaster on loan spreads, such as through disruptions of business operations and physical damage, from the update in lenders' expectations about the future frequency and severity of these disasters.

Our identification strategy instead relies on observing changes in loan spreads for borrowers who are generally exposed to climate change-related disasters but not directly affected by a specific event. We refer to these firms as *indirectly affected* or *at-risk* borrowers. This approach allows us to isolate lenders' updated expectations on the future severity of climate change-related events. The staggered aspect of natural disasters also mitigates the concern about potentially omitted concurrent events.

In our empirical tests, we exploit detailed geographic exposure data on a large cross-section of U.S. borrowers from the National Establishment Time-Series (NETS) database in combination with the Spatial Hazard Events and Losses Database for the United States (SHELDUS). For each borrower, we construct measures of their

[1] Recent studies attribute the increased severity of several natural disasters to climate change. Hurricanes have become increasingly more severe in recent years, and their landfalls have caused increasing damage in the United States (Nordhaus, 2010) and worldwide (Kossin, Knapp, Olander, and Velden, 2020). The 2020 storm season produced a record 29 named Atlantic storms. This pattern holds globally (Webster, Holland, Curry, and Chang, 2005) and it holds true for a range of other types of severe climate change-related weather events (Stern, 2007; Mendelsohn and Saher, 2011). Recent studies have proposed methods that allow for the attribution of individual disasters to climate change. Hansen, Auffhammer, and Solow (2014) directly attribute the increased severity of both floods (Van Der Wiel, Kapnick, Van Oldenborgh, Whan, Philip, Vecchi, Singh, Arrighi, and Cullen, 2017) and hurricanes (Risser and Wehner, 2017; Van Oldenborgh, Van Der Wiel, Sebastian, Singh, Arrighi, Otto, Haustein, Li, Vecchi, and Cullen, 2017) to climate change. The impact of these severe weather episodes is significant and Stern (2007) estimates that by the middle of this century, extreme weather events alone could cost 0.5% to 1% of global GDP annually.

exposure to various types of disasters, as a result of the geographic footprint of their operations. This setup allows us to measure not only the direct impact of disasters that affect borrowers but also borrowers' general exposure to certain types of disasters based on their operations in at-risk regions.

We find that following climate change-related disasters, banks charge higher spreads on loans to *indirectly affected* borrowers with recently high exposure to these types of disasters. This effect varies from 19 basis points for hurricanes to about 8 basis points for wildfires and floods. These changes in loan spreads are economically sizable, as they represent about 5% to 10% of the unconditional spread charged on loans included in the sample.[2]

Consistent with a nonlinear effect related to exposures, the impact on loan spreads is concentrated among borrowers with the largest exposures to these natural disasters. Additionally, the change in loan spreads is strongly related to borrowers' creditworthiness, as firms with higher ex ante credit risk experience greater hikes in loan spreads.

Providing additional support to the relation between severe weather events and climate change, we also find that associated pricing effects appear to be time varying with attention to climate change. The increase in spreads for at-risk borrowers is strongest at times of high media attention to climate change. Consistent with time-varying attention, pricing effects are strongest in the immediate aftermath of an indirect disaster impact, then fade over time. This finding resembles the attention channel that increases the pricing of climate risk in municipal bonds due to more extreme projections of sea level increases in Goldsmith-Pinkham et al. (2019). Further, the reaction in loan spreads is stronger for more severe disasters that tend to be more visible and provide a greater chance for banks to update their beliefs about the severity and frequency of climate change disasters.

This evidence on the link between climate-related risks and loan pricing is not completely surprising, as it is consistent with lenders' awareness of the threats that climate change poses to their loan portfolios. In recent regulatory filings, the 10 largest U.S. banks discuss the link between climate change and certain severe weather incidents, and 8 out of 10 banks mention that climate change (potentially) intensifies these disasters and poses a material risk to the creditworthiness of borrowers (see Appendix Table A.1). Lenders, credit rating agencies and

[2]Though we analyze a comprehensive set of natural disasters individually and jointly, in our baseline specification we focus on hurricanes, as they are by far the world's costliest natural weather disasters, are widely observed and relatively frequent. We show in the appendix that our results carry over to wildfires and floods.

governments are aware of the threat of climate change–related disasters for loans.[3]

Our baseline work focuses on the primary market for syndicated loans, but we also find that climate risks are priced in the secondary market. In this market, we observe a 2.1% decline in loan prices following recent climate change-related natural disasters, providing evidence that climate change affects loan pricing beyond origination. This is important, as it suggests that firms' decision to raise funds does not drive this observed increase in loan spreads. Moreover, this result suggests that investors other than banks also price the climate risk embedded in these types of loans.[4]

As a supplementary analysis, we investigate if the increased risk from climate change related disasters goes beyond specific loan by using banks' internal assessments of the probabilities of default (PDs) of corporate borrowers. These PDs are reported on a quarterly basis by U.S. banks as part of their regulatory filings associated with the Dodd-Frank Act stress tests requirements. We find that banks increase the PDs of *indirectly affected* borrowers after a hurricane by about one percentage point. This is an economically substantial increase, as it represents about one-fifth of a standard deviation for all PDs captured in the sample period. We also find that this increase is persistent for two quarters after the hurricane occurs. This result provides further evidence that banks take into account risks associated with climate change disasters in their risk management approach.

A critical step in our identification strategy is to assess whether our estimates truly reflect lenders' updating views about climate change through its impact on related natural disasters instead of capturing the effect of any type of rare natural disasters on the creditworthiness of at-risk firms. To differentiate these two channels, we repeat our main analysis with a placebo in the form of disasters that are not related to climate change, such as earthquakes. Borrowers with indirect exposure to these non-climate change disasters, measured by both geological potential risk as well as realized risk, experience no change in interest rates in either the primary or secondary loan market or in the internal PDs calculated by banks. Moreover, our estimates hold when we simultaneously

[3]As presented in Appendix Table A.1, banks start to note natural disasters as an important risk. By 2019, all banks in the sample flag those disasters as a material issue and linked them to climate change. For example, PNC Bank's 2019 10-K filing explicitly states, "Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans." Appendix A.2 provides a wide range of examples for this type of awareness of the link between climate change, disasters, and credit risk.

[4]Syndicated term loans are typically transferred to other types of non-bank investors after origination (Lee, Li, Meisenzahl, and Sicilian, 2019). Price changes in the secondary loan market therefore reflect the views of these investors rather than the views of the banks that originally underwrote the loan.

estimate the effects of both climate change-related disasters and disasters unrelated to climate change. Consistent with banks learning about the severity of disasters, the reaction in loan spreads for indirectly affected firms is stronger for more severe disasters.

Another potentially confounding factor with our identification strategy is that banks may internally transfer funds from unaffected regions to those affected by natural disasters (Cortés and Strahan, 2017; He, 2019). The increased interest rates for indirectly affected borrowers could, therefore, simply reflect the decrease in loan supply due to this shift in credit availability. To address this issue, we control for time-varying, bank-specific loan supply conditions in all our specifications. This effectively draws inference from firms that borrow from the same bank at the same time, with the only difference being that one firm is exposed to climate change-related natural disasters and the other firm is not. This setup alleviates concerns about banks' internal liquidity channel driving our results.

An additional concern might be that large-scale disasters ripple through the economy due to customer-supplier links (Barrot and Sauvagnat, 2016). Therefore, we conduct an additional test that directly controls for each borrower's exposure to disasters through their customer-supplier linkages, and find that our estimates are unaffected. Besides these robustness tests, we show that our results are not driven by a host of other factors including the seasonality of natural disasters and lending, alternative measures of operational footprints or disaster exposure, or the relative infrequency of U.S. earthquakes. Neither are results driven by firms in the control group being directly affected by natural disasters. Our results are further robust to various measures of attention and a wide range of model specifications.

Lastly, we assess whether the climate risks priced by lenders force firms to adjust their finances. We find that bank-dependent firms reduce their physical capital expenditure by 0.8%, or about 10% of the unconditional sample mean. At the same time, these firms increase their cash holdings relative to liabilities by about 15% relative to the unconditional sample mean. This finding provides further evidence that climate change-related risks may already affect firms through their cost of funding.

Our paper contributes to the nascent literature on how investors respond to climate change by providing estimates on changes in corporate loan spreads for indirectly affected firms around climate change-related natural disasters. Quantifying the market's perception of climate change is important for corporate borrowers in their long-term capital allocation decisions. To the best of our knowledge, ours is the first study to directly link climate change to present-day corporate loan costs. To date, the evidence for corporations is limited to long-lived assets such as equity securities. Notably, Engle, Giglio, Kelly, Lee, and Stroebel (2021) develop a new measure of climate change risk hedging in portfolios and Ramelli, Wagner, Zeckhauser, and Ziegler (2019) find that investors reward firms that try to mitigate the effects of climate change. Kruttli, Roth Tran, and Watugala (2019) find that markets are effective at pricing the direct effects of extreme weather shocks in stock prices and options. On the bank lending side, de Greiff, Delis, and Ongena (2018) investigate how banks are exposed to regulations that outlaw fossil fuels, which is another type of climate risk typically referred to as *transition risk* (Financial Stability Board, 2020). Similarly, Seltzer, Starks, and Zhu (2020) and Ivanov, Kruttli, and Watugala (2020) find that firms with higher climate regulatory risk, as opposed to actual physical climate risk, face higher bond and loan yields.

The paper most similar to ours is Goldsmith-Pinkham et al. (2019), who investigate how more extreme projections of sea level elevation affect the pricing of municipal bonds. Like us, they investigate the effect of a specific element of climate change on debt securities and they find that sea level increases are priced only very recently and to a small extent. We contribute to this literature by examining how corporate borrowers are affected by risks that emanate from climate change.

Another contribution is that we provide estimates on the credit risk that banks assign to natural disasters related to climate change. This assessment is crucial, as banks will be incentivized to enhance their risk-management practices related to climate risks if severe weather incidents become more intense and more frequent as predicted. In a related manner, the finding that loan spread hikes around climate change-related natural disasters are transitory and driven significantly by attention to climate risks may have consequences from a regulatory perspective. This implies that banks may be inadequately provisioning for potential future climate change-related loan losses, and this can diminish banks' financial resilience and result in economy-wide adverse effects in the future.

2 Hypotheses development

The most straightforward way to test for the effect of climate change-related disasters on borrowing costs is to estimate the change in loan spreads as a function of the direct exposure of a firm to this type of disasters. However, this approach faces the challenge that areas prone to these disasters have seen increasing economic activity in recent years, for example, Florida for hurricanes and California for wildfires (Nordhaus, 2010).[5] In our analytical framework, we overcome this challenge by decomposing the impact of disasters on loan spreads into two parts: (a) the direct results of the disaster (e.g., damages to physical assets, disruptions in the production process and positive effects due to rebuilding efforts) and (b) lenders updating their beliefs about the future frequency and severity of these disasters.

To disentangle the two effects, we isolate shocks to the expected future severity and frequency of climate change related disasters by drawing inference from firms that are at risk from these disasters, but not directly affected at a given point in time. Formally, we test the following hypothesis:

Hypothesis 1: After a climate change-related disaster, banks charge higher loan spreads for at-risk, but unaffected, borrowers.

One potential problem with this setup is that banks might simply update their beliefs on the future exposure of borrowers to any type of rare disaster, unrelated to climate change. Therefore, we contrast these results on climate change-related disasters with non-climate change-related disasters, such as earthquakes. We test the following hypothesis:

Hypothesis 2: For disasters that are not amplified by climate change, there should be no effect on loan spreads for indirectly affected borrowers.

Finally, we hypothesize that time-varying attention to climate change leads to fluctuations in the pricing of climate change-related disaster risk in the corporate loan market. We conduct tests on the following hypothesis:

Hypothesis 3: The pricing of climate change-related disasters is more pronounced when more attention is paid to climate change.

We test these hypotheses using panel estimations with different types of fixed effects and measures of corporate loan risks. Importantly, we construct detailed measures of exposures to climate-related disasters, which we describe

[5] We plot the estimates direct effect of natural disaster hits on loan spreads in Figure 1.

in the next section.

3 Data

A critical aspect of any climate-related physical risk analysis starts with the construction of the data. To assess the exposures of firms to physical risks, we need to construct a dataset composed of different layers. In our study, the first layer captures the exposure of each geographic location (e.g., county) to climate change–related natural disasters and to disasters not linked to climate change. The second layer captures the exposures of each firm to these geographic locations. The final layer captures the exposures of banks to these firms. This section describes the construction of each one of these layers and the data sources used.

3.1 Data on disasters

We obtain data on disasters from SHELDUS, which is a county-level natural hazard data set for the United States. It encompasses information from 1960 to the present. This database provides information on the type of hazard, affected location (county and state), year and month, and the direct losses caused by the hazard (e.g., property and crop losses, injuries, and fatalities). These data are widely used in studies on the effect of natural disasters, including studies on bank lending (Cortés and Strahan, 2017). Our data captures disasters in which the Governor of a state declares a "state of emergency" with a formal request for Federal Emergency Management Agency (FEMA) funds to respond to the disaster. Thus, we include only relatively large disasters. We then classify disasters as being related to climate change based on reports produced by the IPCC (Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi, et al., 2017).[6] These reports find substantial evidence of a link between climate change, heat waves, and wildfires. The report finds similarly strong evidence for a link between climate change and more severe Atlantic hurricanes as well as extreme precipitation. Therefore, we classify hurricanes, floods, and wildfires as climate change related severe weather events.

In our baseline specification, we focus on hurricanes as climate change–related disasters, as they are widely observed, severe, and relatively frequent. We use the SHELDUS data to assess the exposures of each county to

[6] The IPCC is an intergovernmental body of the United Nations, which provides policymakers and the public with regular scientific assessments on climate change, its implications and future risks.

these types of natural disasters and also to capture the realization of these disasters and their impact on specific geographic areas. In Appendix A.4, we show that our results hold for each of these disasters individually as well as a pooled estimation of them jointly. We provide a wide range of evidence from both climate science and general perception of the link between specific disaster types and climate change in Appendix A.3.

We contrast our findings for climate change-related disasters with those that are unrelated to climate change. Among natural disasters, earthquakes are the most clearly unrelated to climate change. Therefore, our main specification uses earthquakes as non–climate change disasters. Since earthquakes are rather infrequent in the U.S. and there have been few in the SHELDUS data, we use seismic hazard site-specific data from the U.S. Geological Survey (USGS) from the Department of the Interior to capture the likelihood that specific locations could be affected by this type of natural disaster. [7] Starting in 1996, the data project potential maximum expected ground motions of latitude/longitude locations across the conterminous United States. These data allow us to construct a detailed county-level assessment of exposures to earthquake hazards. As with the climate change-related disasters, we use the SHELDUS data to capture the realization of earthquakes in the United States. However, given the sparsity of these natural disasters as mentioned previously, we also run an additional robustness test using foreign earthquakes as shocks to attention to earthquakes.

The IPCC also finds that climate change leads to a reduction in the number of incidents of extreme low temperatures, which are coded as *winter weather* in SHELDUS. We, therefore, also conduct tests of winter weather as non-climate change-related disasters.

Figure 2 and Figure 3 provide graphic representations of the exposure of each county to hurricanes and earthquakes, respectively. The maps present snapshots of our time series for 2008, roughly in the middle of our sample period, and they show that our data on disasters reflect the expected distribution, with hurricanes causing damages in the south east and east coast, while seismic ground motions are most active along the west coastal line.

For our empirical tests, we follow a few steps to select and transform the natural disasters data. First, we focus on large disasters with aggregate damages that exceed $100 million in 2019 constant dollars. Second, we calculate county-level exposure to each type of disaster within a rolling 10-year window. Last, we classify counties

[7] The USGS seismic hazard maps and site-specific data are available on https://www.usgs.gov/programs/earthquake-hazards/seismic-hazard-maps-and-site-specific-data.

as *high-exposure* counties if they are in the top 10% of counties with respect to damages for a certain type of disaster within that window.

3.2 Data on firm and bank exposures to natural disasters

After we measure each county's exposure to natural disasters, we next construct granular corporate geographic footprints to quantify each borrower's exposure to climate change–related disasters. Deutsche Bank, in its 2018 white paper, captures this intuition: "Perhaps the most telling metric of a company's climate risk is the location of its assets and their exposure to changing extreme weather patterns. The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks."[8]

We construct detailed geographic footprints of corporations using the NETS dataset from Walls and Associates.[9] We use information at the county-level that captures the number of establishments that a firm has in a given location to create a location-weighted measure of a company's exposure to each disaster type. To do so, we multiply each firm's fraction of establishments in each county by that county's exposure to disasters, arriving at an operations-weighted measure of a firm's exposure to disasters. We then classify a firm as *indirectly exposed* to each type of disaster (e.g., hurricanes) if its operations-weighted exposure to historically disaster-prone counties is in the top quintile of firms.[10] For earthquake exposure, besides measured by historical occurrence based on the SHELDUS data, we also apply each firm's location-weighted ground motion assessment.

In the last layer of our dataset, we add syndicated loan data from Refinitiv's DealScan database and balance sheet and income statement data for firms from S&P Compustat. DealScan provides loan information at origination, including loan amount, loan maturity, and loan spread. We begin our sample in 1996 with the introduction of the SEC's mandatory electronic filing. We include all loans originated in the United States that can be matched with borrowers that appear in the NETS dataset. We use loan amounts in 2019 dollars, adjusting

[8] A detailed overview of this and similar statements by other lenders is presented in Appendix A.2.

[9] The NETS database is constructed using annual snapshots of establishments with Dun and Bradstreet ids (DUNS) as of each January. This dataset contains descriptive information about each establishment starting with its location and parent company, as well as quantitative data such as employment and sales.

[10] We only have access to NETS data up to 2014. In our main sample, we carry forward firms' footprints from 2014 through the end of our sample period in 2019 since these geographic footprints exhibit strong serial correlation. Between loans of the same firm, which are usually spaced apart by about 4 years, the correlation of hurricane exposure is 0.94. All our results remain economically and statistically unchanged if we stop the sample in 2014.

the nominal value using the GDP deflator produced by the Bureau of Economic Analysis. Syndicated loans have one or more lead arrangers and several participating lenders. A lead arranger serves as an administrative agent who has a fiduciary duty to other syndicate members to provide timely information about the borrower, whereas participating lenders are passive investors whose main role is sharing the ownership of a loan. In our empirical tests, we restrict our analysis to lead arrangers. On the borrower side, firms that borrow through syndicated loan arrangements can potentially be directly and indirectly affected by a disaster at a point in time. To avoid our results from being polluted by any potential direct effect of natural disasters, we exclude all loans of those borrowers that have suffered from either hurricanes or earthquakes within 3 months of the loan origination.

As an alternative to the syndicated loan data, we use information on banks' model-based estimates of PDs for commercial borrowers reported in the Federal Reserve's (FR) Y-14Q form. This information is collected as part of the Dodd-Frank Act's stress tests requirements. Bank holding companies with assets above $50 billion between end-2011 and 2018 and above $100 billion thereafter, are required to report this information. The PDs calculated by so-called "advance approaches" banks are based on banks' internal risk models as proposed in the Basel II Accord. For banks that are not subject to the advance approaches regulation, the PDs reported are based on the internal risk ratings of the banks. These PDs are one-year "through-the-cycle" default rates. For our analysis, we focus on publicly-traded U.S. borrowers that receive commercial and industrial loans. PDs are only available after the end of 2014, which restricts our sample to the period between 2014 and 2019.[11]

Table 1 displays summary statistics of loan characteristics and natural disaster property damages. Our sample period is from 1996 to 2019. All variables are calculated as defined in Appendix A.1.

[Table 1 here]

Panel A covers all matched loans in our main test sample. The median loan is a $649.73 million (in 2019 U.S. dollar) credit package with a 5-year maturity and a 150.00 basis points credit spread. More than half of the loans have financial covenants, and around three-fourths of the loans are revolving credit facilities. The median borrower in the sample has $3.60 billion in total assets, with a return on asset (ROA) of 0.12 and a debt-to-asset

[11] We exclude the oil sector, NAICS 211111, from our sample. Oil firms frequently have exposure to hurricanes through production assets such as oil platforms operating outside of U.S. counties, and hence the NETS data does not allow us to correctly identify their exposure. Furthermore, firms in the sector experienced significant financial stress in the 2014-2015 period when oil prices dropped materially.

ratio of 0.33. About 10% of the loans are originated within three months after a hurricane hit. Similarly, about 4% of the loans are originated within three months after an earthquake strike.

Panel B shows disaster damage across disaster types. Hurricanes, flooding, and winter weather affect more than 1,900 counties due to their massive scale. Though their severity varies by type, all the disasters in our sample are considered severe because they were all declared by the President as a major disaster in response to the Governor of the affected states. At the county level, hurricanes and earthquakes are the most destructive disasters, but all types of disasters show significant damage in the tails of the distribution.

Lastly, panel C reports summary statistics for the PDs reported by banks in their FR Y-14Q filings. The sample mean for these PDs is 1.2% with a standard deviation of 5%. The period encompassed by the data is characterized by an economic expansion, which explains the relatively low values for PDs.

4 Climate change and loan pricing

4.1 Empirical setup

As described in section 2, our main objective is to test for the pricing of climate change in loan spreads using borrowers' exposures to natural disasters as part of the identification strategy. A naive approach to capture the pricing of climate change in loans would involve estimating the effect of these natural disasters on loan spreads for firms *directly* exposed to such events. Figure 1 presents this analysis.

[Figure 1 here]

The figure shows the coefficient (and 90% confidence interval) on an indicator variable equal to one for firms directly exposed to climate change-related disasters around the time that one of those events takes place. Loan spreads is the dependent variable in this specification. As shown in the figure, the effect of climate change-related disaster on loans spreads appears to exhibit a small and positive time trend. Compared to the time period of 1996 to 2001, loans issued by firms following a direct disaster hit carry an additional increase in spread by about 20 to 30 basis points from 2006 to 2019. This approach, however, does not allow us to disentangle changes in loan spreads due to the direct effects of the disaster on borrowers' performance from banks' pricing of the change in the frequency and intensity of these disasters due to climate change.

For example, damages from hurricanes have increased partly because more people live in hurricane-prone areas that contain more valuable property (Pielke Jr, Gratz, Landsea, Collins, Saunders, and Musulin, 2008). Direct exposures to large weather events can have widespread effects on economic and business activity (Dell, Jones, and Olken, 2014), making it difficult to isolate the change in banks' beliefs about climate change from their expectations about potential rebuilding efforts associated with these disasters.

To disentangle these two separate effects of natural disasters on loan pricing, we do not draw inferences from firms that are actually hit by these events; instead, we draw inferences from firms that are at risk from climate change-related disasters but that do not experience any damages in a given disaster event.

Intuitively, we hypothesize that banks learn about the increased severity of climate change-related disasters by following the scientific studies on this topic and by observing the effect of these events on loan performance. Consider a hypothetical case in which a bank lends money to a borrower who has major operations in a hurricane-prone region such as Florida. When hurricane Harvey struck Houston in 2017, this borrower was not directly affected by the damage. However, if the bank updates its prior expectations regarding the severity of hurricanes after observing Harvey, the bank may charge a risk premium for the next loan granted to this hypothetical borrower in Florida. Formally, we use the following econometric setup to test *Hypothesis 1*:

$$\begin{aligned} Spread_{i,m,t} = {} & \beta_1 Indirect\ hurricane_{i,t} \times Recent\ hurricane_t + \beta_2 Indirect\ hurricane_{i,t} + \\ & \beta_3 Recent\ hurricane_t + \gamma X_{i,m,t} + \alpha_i + \phi_{m,y} + \epsilon_{i,m,t} \quad (1) \end{aligned}$$

The outcome variable of interest is the loan spread charged to borrower i by bank m in month t. Our main coefficient of interest is β_1. It measures the effect of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ on loan spreads, which is the interaction of our time-varying measure of firm i's exposure to hurricanes and an indicator of a recent hurricane in the past quarter. We expect β_1 to be positive if banks update their prior expectations about the severity of climate change-related disasters after observing them.

Importantly, we need to control for other factors that may influence loan spreads but are not associated with changes in the climate and its effect on natural disasters. For example, greater exposure to climate change disasters might reflect borrowers' time-varying preferences for riskier locations (e.g., expansion into new markets that are at-risk of natural disasters). To take this into account, we control for $Indirect\ hurricane_{i,t}$ which should capture that type of risk taking. Similarly, the indicator *recent hurricane* takes the value of one if a climate change-related disaster has occurred within the 3-months prior to loan origination. It is not absorbed in the year fixed effects and captures the average association between the realization of these disasters and loan spreads. Since most of our sample of firms has geographically far-flung operations, the most severe natural disasters (e.g., hurricanes) have at least a small impact on many borrowers. We therefore drop all loans taken out by borrowers who are directly affected by a hurricane or earthquake in the quarter of the loan. In additional robustness checks, we also add a direct control for the direct exposure to all other disasters. Finally, we include $X_{i,j,t}$, a vector that reflects a wide range of time-varying firm controls (e.g., size, profitability, debt-to-asset ratio) and loan controls (e.g., loan type, maturity, covenants).

Besides controls for observable characteristics, we include borrower fixed effects (α_i) to absorb any unobservable time-invariant characteristics of the firms in our sample. In effect, the fixed effects allow us to compare two loans obtained by the same borrower at two different points in time: one loan obtained during normal times and another loan obtained after a recent natural disaster that indirectly affected the borrower. Importantly, these borrower fixed effects allow us to control for a number of alternative explanations, such as the geographic location of a firm's operation, or the industry in which it operates.

Another potentially confounding channel, this time from the lender's perspective, is the potential use of internal-funding across branches by banks. Major disasters may drain funds from branches of a bank in an affected location, which may lead the bank to transfer funds from branches in unaffected locations, reducing their funding, and to an increase in the loan spreads charged to unaffected borrowers (Cortés and Strahan, 2017). We therefore include bank $\times$ year fixed effects ($\phi_{m,y}$) in our regressions to capture the time-varying nature of these internal funding markets.[12] Intuitively, this means we are comparing two borrowers from the same bank, in the same year, and the only difference between them is the borrower's indirect exposure to a recent climate

[12] Our results remain economically and statistically almost identical when we include additional quarter fixed effects to account for seasonality in the syndicated loan market (Murfin and Petersen, 2016).

change-related disaster.[13] We cluster the standard errors ϵ two ways. First is by firm, to capture serial correlation of errors within the same borrower over time. Second is by year, to capture arbitrary correlation of errors for loans taken out at the same point of time.

4.2 Climate change and loan pricing

Table 2 presents the results from estimating various forms of Equation 1. These estimations provide a direct tests of our *Hypothesis 1.*

[Table 2 here]

The key coefficient in this specification is β_1, which captures banks' pricing of climate change through their assessment of the impact of climate-related natural disasters on the loan spreads charged to firms that are indirectly exposed to these events. In column 1 of Table 2, the coefficient estimate of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ is 17.3 and is statistically significant at the 5% level. After a climate change-related disaster, banks raise interest rates spreads by about 17 basis points to exposed unaffected borrowers. The economic magnitude of this effect is sizeable and comparable to a credit rating downgrade of about two notches.

In column 2, we add loan-level controls for maturity, loan type, and the presence of financial covenants. Our main coefficient estimate remains economically and statistically very similar, at about 18.8. The same is true when we replace these loan controls with firm-level control variables that capture time-varying firm-level credit quality in column 3. These controls include profitability, leverage, and credit rating. The estimate for β_1 in this setting is 19.2. Column 4 presents our most complete specification, which includes the full set of fixed effects, bank controls, and loan controls. The coefficient estimate of β_1 in this specification is about 18.8, which is economically material.

Taken together, the results in Table 2 imply that banks update their expectations regarding increased future damage from climate change disasters by increasing the interest rate spread charged to borrowers who have significant exposure to these disasters.

An important concern is that these estimates just reflect an update of banks' perception of the effect of any type of infrequent disasters on firms' creditworthiness and are not particularly associated with an assessment of

[13] Most loans in our sample are syndicated. We assign each loan to its lead arranger to capture the loan supply effect.

the potential impact of climate change on borrowers. As we note in *Hypothesis 2*, if the pricing effects we are capturing in our specifications truly reflect the effect of climate change, the occurrence of *non-climate change-related disasters* should not lead to adjusted prices in at-risk borrowers' loan spreads. To test this, Table 3 repeats the analysis from Table 2, but it replaces our measures of direct and indirect exposure to hurricanes with analogous measures for non-climate change disasters, i.e., earthquakes.[14] One potential concern could be that the small numbers of earthquake strikes in the United States as captured by the disaster frequencies in Table 1 during our sample period make comparisons between U.S. hurricanes and U.S. earthquakes difficult. As described in section 3, we address this concern by constructing firms' exposures to earthquakes by using their location-weighted ground motion assessment, which is based on the USGS's seismic hazard maps. This measure captures each location's ex-ante potential for ground shaking due to earthquakes.

[Table 3 here]

The coefficients of interest in Table 3 are those on the interaction term $Indirect\ earthquake_{i,t} \times recent\ earthquake_t$. In this particular set of tests, *Recent earthquake* takes the value of one if an earthquake materialized in the United States in the previous three months. In column 1, the coefficient estimate is statistically insignificant and actually negative, in contrast to the positive coefficient on hurricanes of about +18 basis points. As we add controls for firm- and loan-level variables in columns 2 through 4, the coefficient estimates on this interaction term remain statistically insignificant and negative throughout.[15]

One potential concern could be that there were no major earthquakes inside the United States during our sample period, making comparisons between U.S. hurricanes and U.S. earthquakes difficult. In Appendix Table A.3, we get similar results when using each firm's total footprints in counties hit by earthquakes in history as the new measure of indirect earthquake exposure. In Appendix Table A.3 we replace domestic earthquakes with the

[14] As described in section 3, we follow the IPCC assessment when classifying hurricanes, wildfires and floods as climate change-related disasters, and earthquakes and winter weather as disasters unrelated to climate change. Our results are consistent in regressions for each type of disaster, shown in Appendix A.4. All our results are robust to using each disaster individually as well as pooling climate change disasters and non–climate change disasters together.

[15] The coefficient estimates across specifications are insignificant but economically quite meaningful. One potential explanation could be that earthquakes disasters in general and earthquakes in particular do not just allow for updating on the severity and frequency of disasters, but also other factors. These include the quality of mitigation efforts (Earthquake proof buildings, flood walls and levies) and the reaction of emergency services (e.g. fire fighters). While we do not want to over interpret these coefficients, one plausible explanation could be that lenders update positively on the success of mitigation measures against earthquakes. This would also explain why the coefficients are economically zero when it comes to earthquakes abroad in the appendix, since investors don't learn about U.S. mitigation from these foreign quakes.

thirteen most devastating global earthquakes (in terms of damages) during our sample period.[16] Again there is no effect on the risk premium charged for loans of at-risk, domestic firms in any specification.

These results on the relation between earthquakes and loan spreads support our interpretation of the results in Table 2. Climate change is associated with an intensification of certain types of disasters over time. Banks observe the scientific evidence on this association and the actual increase in the severity of these disasters and update the spread for at-risk borrowers accordingly. This reflects their implicit pricing of climate change. While non-climate change disasters are similarly devastating for borrowers, they do not intensify over time, thus banks already price them correctly in their loans and no adjustment in spreads is needed.

In an additional test, we rule out the possibility that our results are driven by the potential simultaneous occurrence of a climate change disaster and a non-climate change disaster. In Appendix Table A.5, we simultaneously include measures of both climate change (e.g., hurricanes) and non-climate change disasters (e.g., earthquakes) in our loan spreads specification. As in our main analysis, we find that the effect of climate change disasters on firms with general exposure to these disasters is associated with a statistically and economically large increase in interest rate spreads of about 19 basis points. As in the analysis in Table 3, the coefficient on $Indirect\ earthquake_{i,t} \times Recent\ earthquake_t$ is negative and statistically insignificant throughout all specifications.

These results support the idea that banks learn about the increasing severity of climate change disasters and accordingly increase the spreads charged to borrowers who are at risk for these disasters, consistent with *Hypothesis 1*. We also find support for *Hypothesis 2*, as banks do not seem to price indirect exposures to natural disasters not associated with climate change.

4.3 Cross sectional effects on high-risk borrowers

Increased borrower risk hurts banks mostly through the threat of default. A financially healthy borrower can weather the damage from a climate change disaster with no impact on their ability to repay their debt. In contrast, borrowers who are close to bankruptcy have the highest risk of defaulting on loans as a result of their exposure to a climate change disaster. If banks indeed price the increased risk from climate change disasters, the

[16] These earthquakes include such high profile cases as the 2004 south east Asia quake that caused an estimated 230,000 fatalities, the 2010 Haiti quake with an estimated 250,000 fatalities, and the 2011 Tohoku quake followed by the Fukushima nuclear reactor meltdown and more than 10,000 fatalities.

price reaction should be more pronounced among borrowers who are more at risk of bankruptcy. We empirically test this conjecture in Table 4 using three proxies for borrower risk.

[Table 4 here]

First, in column 1, we estimate the most saturated model of Table 2, column 4, and we interact *Indirect hurricane* $\times$*Recent hurricane* with *Market leverage*, firms' leverage level at the time of loan origination. As before, for ease of exposition, we do not tabulate the lower interactions and control variables of each regression. The interaction term *Indirect hurricane* $\times$ *Recent hurricane* $\times$ *Market leverage* captures the differential effect of an indirect hurricane impact on firms with elevated credit risk. We normalize market leverage such that the coefficient can be interpreted as the effect of a one standard deviation increase in leverage. Consistent with banks reacting more strongly when borrowers are less financially stable, we find that the coefficient on the triple interaction is 25.3, while the double interaction term *Indirect hurricane* $\times$ *Recent hurricane* stays around 17.5. The effect on highly leveraged borrowers is therefore more than twice as large as the effect for the overall sample. This result suggests that banks price climate change disaster risk more acutely for levered at-risk borrowers.

One specific way through which natural disasters threaten firms' creditworthiness is through the threat of destroying physical assets, particularly as those can secure loans. In column 2, we estimate the coefficient for the triple interaction term *Indirect hurricane* $\times$ *Recent hurricane* $\times$ *Tangibility*, where *Tangibility* captures borrowers (normalized) tangibility of assets. Consistent with the threat to physical assets amplifying the effect of hurricanes, the coefficient estimate on the triple interaction is 14, which is statistically and economically significant.

In column 3, we measure borrowers' creditworthiness through credit ratings. The indicator *Non–investment grade* takes the value of 1 for firms rated below investment grade (BBB). The coefficient on the interaction term *Indirect hurricane* $\times$ *Recent hurricane* $\times$ *Non–investment grade* is 46. Again, this result is consistent with banks pricing climate change risk more intensely when the shocks from climate change disasters are more likely to affect borrowers' ability to repay.[17]

These tests support the conjecture that banks are particularly sensitive to increased climate change disaster risk when it is more likely that borrowers cannot absorb these risks, and these risks eventually accrue to the

[17] Note that Compustat stops covering credit ratings after the second quarter of 2018, which limits our sample somewhat towards the end in this test.

lender.

4.4 The severity of natural disasters

If climate change affects both the frequency and severity of disasters, then lenders should react more strongly to more sizeable disasters for two reasons. First, more severe disasters are more widely observed, thus the likelihood of those events being priced is higher. Since we estimate the effect of disasters on indirectly affected borrowers, if lenders fail to observe smaller disasters, they might potentially fail to update their risk assessments as those types of events occur. The second channel linking climate change-related disaster size to loan pricing is through an update of lenders expectations about the trend in disaster magnitude. Since climate change disaster damage has both a random component and a time trend component, lenders can more easily infer a trend in increasing disaster strength for large disasters, while they might assign damage to random fluctuations for smaller disasters. Ultimately, we cannot differentiate between these two explanations, but either one predicts that major disasters should be associated with more significant pricing effects, which should capture information about lenders assessment of the impact of climate change on these types of events.

We test this conjecture in Table 5. In our main analysis, we consider hurricanes that caused cumulative damage in excess of $100 million to define our measure of disaster exposure, and compare them to all the other hurricanes used in our sample. [18] Specifically, we focus on the distinction between regular hurricanes and three super storms with particularly wide-ranging damages exceeding $100 billion: hurricane Katrina, hurricane Maria, and hurricane Harvey. Table 5 presents the results.

[Table 5 here]

Column 1 shows that large hurricanes are associated with rate increases that are 31 basis points, about twice the effect of normal hurricanes which are associated with rate increases of about 16 basis points, similar to our main results, in column 2. These results stay unchanged when we estimate them jointly in column 3. Both hurricanes Katrina and Harvey were the most devastating hurricanes recorded at their time, meaning they provided

[18] In Appendix Table A.2, we calculate our measure of exposure for cutoffs of $50 million, $100 million and $200 million for our pooled sample of climate change related disasters. As in the case of hurricanes alone, larger disasters are associated with stronger increases in credit spreads.

particularly stark data points for lenders to update their risk assessments. Consistent with this interpretation, lenders increase spreads for at-risk, but unaffected, borrowers more starkly after those storms.

4.5 Climate change risk in the secondary market

In this section, we investigate whether the increasing severity of climate change disasters affects loan pricing not only at origination but also in the secondary market. Information about the loans observed in the primary market reflect the firms' decision to raise capital and the lender's assessment of risk at the time of origination. A high loan spread at the time of the initial borrowing could therefore be partially explained by selection concerns. On the one hand, at-risk borrowers might avoid raising debt after a disaster, hoping that financing conditions will be more favorable in the future. Then, those who raise capital at that point are the borrowers most desperate for capital, which is why they pay a higher risk premium. On the other hand, it could be that indirectly affected borrowers are shut out of credit markets, and they are unable to raise capital at any price for a while. This would mean that only economically stronger borrowers can access capital markets shortly after an indirect disaster strike. In this case, higher spreads for newly originated loans in our main analysis would underestimate the true effect of disasters. Which of these two forces prevails is ultimately an empirical question.

To investigate how selection in the primary loan markets affects our results, we turn to the pricing of loans in the *secondary* market. Since these are prices for outstanding loans, there are no selection concerns. We obtain secondary market loan prices from Refinitiv's Loan Pricing Corporation. The secondary market data consist of self-reported information from brokers who quote daily prices on loans. The volume of trading in the secondary market has increased substantially in recent years (Beyhaghi and Ehsani, 2017), and we can obtain the pricing information for 1,737 loans from 2001 to 2018. The secondary loan market is generally illiquid. While brokers quote daily prices, there is no information on whether trades actually occurred. To avoid drawing inferences from stale prices, we aggregate quotes for each loan at the weekly level. Then, in an event study setting, we test the price reaction of these loans for firms that suffer an indirect impact of a natural disaster.

[Table 6 here]

In Table 6, the outcome variable is the logarithmic of each existing loan's weekly average quote price. In column 2, we add loan fixed effects, which capture the average discount at which a loan is trading relative to par. In column 3, we control for year fixed effects to capture time variation in secondary loan prices. Finally, in column 4, our regressions control for both observable and unobservable loan characteristics through loan fixed effects as well as time effects through year fixed effects. To ensure our results are not driven by within-loan time trends in prices, we cluster standard errors at the loan level.

The results in Table 6 confirm our findings from the study of loan spreads at origination. Across the columns, the secondary market loan prices of at-risk, but unaffected borrowers drop by between two and three percent after a hurricane, which is equivalent to an increase in yield. These results show that investors in the secondary market price climate change risk as a result of increasingly severe natural disasters. The economic magnitude of these estimates is significantly larger than the estimates of the primary loan market. A back-of-the-envelope calculation that links changes in yields to changes in prices suggests that an increase in the annual yield of about 18 bps, taken at the median loan maturity of about five years, translates to a naive change in the loan price of about one percentage point. The estimates from the secondary market are about two times as large as those from the primary market. This finding suggests that there is some selection in the primary loan market, since the most severely affected borrowers do not originate new loans shortly after a disaster, either voluntarily or because they are excluded from the market. Consistent with this interpretation, in unreported results, we find a substantial drop in liquidity in the secondary loan market following climate change disasters, with bid–ask spreads widening above their normal level.[19] Jointly, these findings from the secondary loan market not only provide an independent verification of our primary loan market results but also hint at the negative effect of climate change disasters on loan *access*, which goes beyond our main results on loan *pricing*.

4.6 Climate change risk and banks' assessment of default probabilities

Another way of assessing whether our results are impacted by sample selection is by analyzing banks' assessments about the creditworthiness of corporate borrowers by using "credit register" information. We use PDs reported by large U.S. banks as part of their regulatory filings for their corporate borrowers. PDs should be reflected in loan spreads, as they capture the banks "through-the-cycle" expectations of a borrower's likelihood of default.

[19]Unfortunately, our data do not allow us to directly observe trading volume, which would be a more direct measure of liquidity.

The data collected through the FR Y-14Q form allows us to track the PDs assigned by large U.S. lenders to each individual borrower on a quarterly basis. Thus, we can assess if the PDs for the borrowers that are "at-risks" from climate change-related natural disasters experience persistence changes by their lenders.

In Table 7, we present a specification similar to the one used to analyze the secondary loan pricing data, but using the banks' internally generated PDs as the dependent variable. In this specification, we can track the same bank-borrower pairs over time, so there is no issues related to the sample's composition. However, different from the tests using syndicated loan data originations, the sample period is much shorter, end-2014 to end-2019, due to data availability, which limits power. As in the previous estimation, the coefficient of interest is on the interaction term $Indirect\ hurricane \times Recent\ hurricane$.[20] In addition to the contemporaneous effect, presented in columns 1 and 2, we also assess the persistence after two quarter, which we present in column 3. Columns 2 and 3, in addition to firm and $Bank \times Year - Quarter\ FE$ include time-varying firm controls.

As shown in columns 1 and 2, banks increase the PDs of "at-risk" borrowers between 0.8 and 1.1 percentage points after a hurricane occurrence. That reaction is economically important, as it represents about one-fifth of a standard deviation for the PDs captured in the sample. In column 3, we add interacted variables that capture the persistence of the effects of these events on PDs after two quarters. We find that these effects are persistent and statistically significant, as shown by the sum of coefficient presented at the bottom of the table. After two quarters, the cumulative change in PDs is about 1.2 percentage points higher than prior to the hurricane, or 50% larger relative to the first-month adjustment in column 2.

These results provide additional evidence that banks take into account natural disaster risks associated with climate change in their risk management; especially in recent years as attention to this topic has increased.[21]

4.7 Alternative economic explanations

Our results, which show that banks adjust their loan spreads for borrowers exposed to climate change-related disasters, could be explained by other alternative channels that are not related to banks' perception about climate change. We explore some of those alternative channels in this section and assess the robustness of our findings.

[20]In this specification, and due to the shorter period of time, we define at-risk counties as those that fall in the top 30 percent of the distribution.

[21]In unreported results, we show that PDs of "at-risk" firms do not change significantly after the advent of non-climate related disasters, such as earthquakes. This is consistent with the findings using syndicated loan data.

First, the reaction we find on the spreads of "at-risk" firms could be driven by an internal-funding channel in which banks ration credit and increase loan spreads to borrowers in unaffected areas to supply credit to directly affected borrowers (Cortés and Strahan, 2017). While our $Bank \times year$ fixed effects in the main specification absorb these contemporaneous shocks, we conduct an exercise in Table 8 in which we explicitly control for banks' disaster exposure. Table 8 repeats our primary specification with fixed effects (columns 1 and 3) as well as the complete specification including loan and firm controls (columns 2 and 4).

[Table 8 here]

Importantly, these specifications control for the lender's exposure to disasters both in the form of the total number of affected loans (columns 1 and 2) and the total loan origination amount of affected loans (columns 3 and 4). We find that our estimates for $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ remain economically and statistically almost unchanged from the estimates in Table 2, at around 14 to 18. The estimate for our measures of bank exposure is about 3 and statistically significant in columns 1 and 3. Therefore, while some evidence shows that banks increase loan spreads after natural disasters, our results suggest that this increase does not drive the increased spread for borrowers who are *indirectly* exposed to climate change disasters.

Another potential explanation for our results could be that the increase in spreads for "at-risk" firms reflects disaster spillovers across supply chains (Barrot and Sauvagnat, 2016). Table 9 tests this conjecture using data from (Barrot and Sauvagnat, 2016) on specific customer-supplier links to quantify the degree to which borrowers are affected by disasters through their supply chains. As before, odd (even) columns present estimates from the fixed effects only (with firm and loan controls) specifications.

[Table 9 here]

We control for customer exposure (columns 1 and 2), supplier exposure (columns 3 and 4), and both (columns 5 and 6). In all specifications, the magnitude of our main coefficient estimate $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ remains between 14 and 17 basis points. Thus, exposures to disasters (for both customers and suppliers) do not appear to affect our coefficients of interest in a statistically significant way in any of the saturated specifications. These results alleviate concerns that our estimates capture the network ripple effects caused by natural disasters along the supply chain.

An additional channel that could explain our results is the seasonality of hurricanes. Since earthquakes do not follow a seasonal pattern, one might think that borrowers that issue a loan during hurricane season face a risk premium since lenders do not know if a hurricane might strike the borrower soon after. To rule out this alternative explanation, in Appendix Table A.6 we explicitly exclude all loans made during hurricane season, i.e. June through November, each year. We find that our estimated coefficient on *indirect hurricane* × *recent hurricane* is, if anything, amplified by this restriction. The robustness of our results to this test is not surprising, since our definition of *recent hurricane* as a lagged 3-month window means that many treated loans are actually made *after* the hurricane season is over.[22]

4.8 Additional robustness tests

We perform a series of additional tests starting with alternative data definitions. These robustness checks are reported in Appendix A.4.

First, one concern could be that our sample period features no major earthquakes in the U.S., and the relative absence of major shocks may explain our finding in Table 3, rather than the fact that banks do not update their expectations about the frequency and severity of non-climate change related disasters. To rule out this explanation, we conduct a robustness exercise in Appendix Table A.3 in which we define *recent earthquake abroad* using the 13 largest earthquakes globally since the year 1996. These disasters include some of the most destructive, high-profile events including the 2004 Sumatra earthquake that caused the Boxing Day Tsunamis, the 2011 Tohoku earthquake followed by the nuclear emergency in Fukushima, and the 2010 Haiti earthquake. If our non-results in Table 3 are due to the small size of events in the U.S., these major earthquakes should elicit a strong pricing reaction. However, the results in Appendix Table A.3 are economically zero and statistically insignificant in all specifications. This result supports our interpretation that the increased spreads following climate change related disasters reflect an update in lenders' expectation on the frequency and severity of disasters due to climate change, whereas non-climate change related disasters do not elicit updating.

One remaining concern could be that earthquakes are rare in the U.S. during our sample, and the rolling

[22]In addition, seasonality is unlikely to drive our result since most loans have a maturity of multiple years, meaning that all loans include multiple hurricane seasons during their lifetime. Seasonality in loan issuance patterns is also unlikely to explain our secondary market results. Lastly, our placebo test on winter weather in Appendix Table A.9 should be affected by seasonality as much as hurricanes, and we find that the results are different as those for hurricanes.

ten–year classification for at–risk counties might not truly capture the earthquake exposure. In Appendix Table A.4, we re-estimate our earthquake test with an infinite window. We find that the double interaction between recent hurricanes and indirect hurricane exposure measured this way is still statistically insignificant as in Table 3.

Next, we repeat our main analysis separately for each climate change disaster and non-climate change disaster. Following the IPCC, we classify floods and wildfires as disasters that have increased in severity due to climate change. Appendix Tables A.7 and A.8 show that our results are robust to using these alternative natural disasters in an individual regression setting. The coefficient estimates on $Indirect\ flood_{i,t} \times Recent\ flood_t$ is larger than 10 across the various specifications, which translates into a 10 basis point effect, and the coefficient estimate on $Indirect\ fire_{i,t} \times Recent\ fire_t$ is very similar at about 8.5 on average. Both estimates are positive and comparable to the coefficient estimate for hurricanes in our main Table 2, and their smaller absolute size likely reflects the relatively lower damages caused by these disasters compared to hurricanes. Similarly, we consider severe winter weather as a non-climate change related disasters, in accordance with the IPCC. The coefficient estimate on $Indirect\ winter\ weather_{i,t} \times Recent\ winter\ weather_t$ in Appendix Table A.9 is negative and is both economically and statistically insignificant, just like the coefficient estimate on earthquakes in Table 3.

We also pool climate change and non-climate change disasters in two separate aggregates and estimate our standard specification using these measures instead of the proxies for individual disasters. Table A.10 reports the coefficient estimates obtained from this process for the first group consisting of hurricanes, wildfires, and floods. The coefficient estimate on $Indirectdisasters \times Recentdisasters$ ranges from 7.37 to 10.03 basis points. Similarly, Table A.11 shows that the second group consisting of earthquakes and winter weather yields a coefficient estimate that is statistically insignificant. Appendix Table A.5 shows that these patterns hold when we jointly estimate coefficients on the two groups.

While hurricanes are major natural disasters, most of the other disasters can often cause less damage. This difference allows us to estimate the differential effect of disaster size on loan pricing reactions with more granularity than in Table 5. In Appendix Table A.2, we estimate the effect of $Indirectdisasters \times recentdisasters$ for disasters that inflict a minimum of \$50 million, \$100 million, and \$200 million in damage, respectively. We find that the coefficient estimates increase monotonically with disaster size: 3 for disasters with \$50 million in damages, 6 for

$100 million disasters, and 9 for $200 million disasters.

We also implement a set of additional sample selection robustness tests in the Appendix. We first show that our results are not driven by the cyclicality of hurricane seasons by including Bank × hurricane-season fixed effects, nor by specific business cycles in industries operating in hurricane prone areas by including industry × year-quarter FE. Both of these tests, displayed in Appendix Table A.12, yield coefficient estimates that are economically and statistically stronger than those in our main specification. In Appendix Table A.13 we show that our results are robust to excluding loans taken out by firms suffering any type of direct disaster damage in a given quarter.

We then modify our measure of firms' geographic footprint by focusing on employment, rather than business locations. We estimate our main test using this modified exposure measure in Appendix Table A.14. The coefficient estimate on Indirect hurricane (employment) × recent hurricane is comparable, though economically slightly smaller than in our main specification, at 13 to 15 basis points.

We then show that our results are not driven by the credit market freeze during the financial crisis. We drop all observations from July 2007 to July 2009 in Appendix Table A.15, and find that our results remain economically and statistically very similar to the main specification.

Finally, in Appendix Table A.16, we estimate our main specification with different definitions of hurricane exposure. In column 1, we sort firms into quintiles based on the general sample of firms each year, rather than the sample of firms issuing loans in a given year. In column 2, we replace the indicator for the highest quintile of this measure with its continuous version. In column 3, we do the same continuous estimation for our main measure of indirect exposure (quintiles based on firms issuing loans each year), and in column 4, we replace the top quintile measure with an indicator for any hurricane exposure at all (which is effectively an above-median indicator since about half of our firms have zero hurricane exposure). Our results are economically and statistically very similar to our main specification in each of these tests.

5 Time-varying attention to climate change and loan pricing

Banks' ability to correctly price climate change risk depends on their ability to observe it, and there is extensive evidence that investor attention is limited and can be focused by major events. Hypothesis 3 states that the pricing of climate change related risk should be amplified in periods of high attention to climate change. Therefore, we test for time variation in banks' pricing of climate change-induced lending risk. Specifically, we use the Wall Street Journal (WSJ) index introduced in Engle et al. (2021) to measure time varying attention to climate change.[23]

We present results focused on the time-varying nature of climate change pricing in Table 10. These test are similar to those in our main specification, except for the addition of triple interactions including or standard regressors $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ and measures of climate change attention, including the WSJ index. We expect the coefficient estimate on these interaction term to be positive if banks pay more attention to climate change following periods of attention to climate developments and adjust their interest rates more aggressively for borrowers with exposure to climate change disasters.

[Table 10 here]

In column 1 of Table 10, we find that the estimated coefficient on the triple interaction $Indirect\ hurricane_{i,t} \times recent\ hurricane_t \times WSJ\ index$, where $WSJ\ index$ is the standardized version of the index in Engle et al. (2021), is indeed positive at 41.7 and statistically significant at the 5% level. Our main coefficient on $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ remains statistically and economically very similar to our main specification, at 16.6. This result suggests that banks update their loan spreads more decisively in times of high public attention to climate change.

In columns 2 and 3, we split the *WSJ Index* attention measure into medians and terciles, respectively, and find that the pricing reaction increases monotonically in the attention to climate change.

As alternative measures of investor attention to climate change, we obtain data on search traffic from google for the term "climate change". The data span from 2004 to 2020, and in Appendix Table A.17 we re-estimate our findings from the WSJ attention index with this alternative measure of attention. We also construct another index based on news reports captured in Refinitiv's Machine Readable News (MRN) Reuters Daily News Feed database,

[23] The index measures the frequency in which climate change vocabulary appears in the WSJ. It captures overall market attention to the topic and spikes during times of particular attention, e.g. during international summits such as the Paris Climate Agreement in 2015 or the Copenhagen Climate Change Conference in 2009.

and specifically measure the connection between climate change and storms described in these articles, with results in Appendix Table A.18. We find that all our results remain robust, with pricing effects being particularly pronounced in times of generally high attention to the relation between climate change and hurricanes.

As a final alternative measure of attention, in Appendix Table A.19, we use the recent publication of IPCC reports as proxies for public attention. These reports are published about once every seven years. Our sample features three reports in 2001, 2007, and 2014. We define periods of high attention as the two years following each major report and estimate a triple interaction between an indicator for these years and our main specification.[24] We find that loan spreads spike substantially more after a hurricane during those years of high attention, with the coefficient estimate on the triple interaction ranging from 87 to 96 basis points.

To further investigate whether attention to climate change disasters is time varying, we directly estimate the development of loan spreads relative to an (indirect) climate change disaster shock. Table 11 presents the results of dynamically estimating our main model.

[Table 11 here]

The coefficient of interest is $Indirect\ hurricane \times recent\ hurricane\ (t\ quarters\ prior)$, which is the interaction of two indicators: one indicator that takes the value of 1 for firms that were classified as having a high exposure to hurricanes and another indicator for the recent occurrence of a hurricane t quarters before the loan was issued. Analogously, $recent\ hurricane\ (t\ quarters\ future)$ is an indicator for loans taken out t quarters before a hurricane strikes. The results in Table 11 are consistent with time-varying, transient attention to climate change: the coefficient estimate is positive and statistically significant for the quarter in which the hurricane strikes and also for the subsequent four quarters, but this effect vanishes quickly. These findings are consistent with salient information processing by lenders, similar to CEOs overreacting to direct impacts of natural disasters (Dessaint and Matray, 2017). Notably, the effect in secondary markets seems to be more transient than in banks' credit risk assessments in Section 4.6.

This raises the question whether the increased loan spreads that we observe reflect this type of overreaction, or whether the transitory price reaction we observe in both primary and secondary markets reflects a correct initial assessment of increased risk, with a subsequent fading due to short memory. In our next test, we investigate this

[24]No major hurricanes occur ed during the 12 months after each report.

question by testing if the direct damages from hurricanes increase for firms after an indirect hit. If indirect hits act as "warning shots" which tell lenders about the likely future increase in *direct* hits, then firms with *indirect* disaster hits should subsequently see a rise in *direct* damages from disasters. If indirect hits carry no information about the future frequency and severity of disasters, there should be no subsequent increase in direct disaster exposure.

To test this conjecture, we construct a firm-month panel of all our sample firms. We then run regressions of different measures of direct hurricane damage on *Previous direct hit*, an indicator taking value of one for each firm in each month after their first indirect hit. The results are displayed in Table 12.

[Table 12 here]

The independent variable in column 1 is an indicator for whether a firm suffers any type of direct hurricane damage in a given month, measured as the percentage of firms' operations in directly hit counties. Column 2 replaces this with an indicator for damage in the top quintile of the direct hurricane damage distribution, and the dependent variable in column 3 is the total operations in directly hit hurricane counties as a continuous quintiles variable. Across all three specifications, we find a robust and economically significant relationship between indirect hits and future direct damages. Compared to the unconditional mean, the coefficient in column 1 implies a 50% increase in the chance of direct hurricane damage. The coefficient in column 2 is even more economically relevant: the estimated 2.4% increase in the likelihood of severe hurricane damage represents an almost 80% increase relative to the unconditional change of suffering large direct hits each month.

Importantly, indirect hits in the last 12 months have predictive power for future direct hits even after controlling for the firms' geographic exposure to general hurricanes through *indirect hurricane*. This could imply that hurricanes hit more severely, or in previously safe areas over time. Taken together, these results suggest that indirect hurricane hits can indeed be interpreted as "warning shots" that predict future direct damages from hurricanes.

6 Corporate finance effects of climate change risk

In our final set of tests, we investigate whether climate change-induced risks affect corporate investment and cash holdings. To do so, we construct an annual panel of corporate investments and cash holdings and estimate a model that links investment and cash holdings to indirect impacts from climate disasters. Our outcome variable is the investment ratio, i.e., the ratio of each firm's investments to its assets, as well as cash holdings as a fraction of liabilities. We present the results in Table 13.

[Table 13 here]

We hypothesize that those firms that are most dependent on bank financing will react most severely to an indirect climate change disaster shock. As before, we identify these firms by their lack of an investment-grade credit rating. These firms also experience the largest increase in financing costs, as shown in Table 4.

Our results are consistent with climate change disasters having effects on the corporate finance decision of firms. In columns 1 and 2 of Table 13, we investigate corporate investment. Our models are saturated with firm- and year fixed effects. We find that, after an indirect hurricane strike, non-investment grade firms reduce their relative investment by about 0.85% compared to the same firm's investment in other years, with the coefficient statistically significant at the 1% level. This is an economically sizeable effect of about 10% compared to the unconditional mean.

Finally, in columns 3 and 4, we investigate whether lower investment by especially affected firms is accompanied by higher precautionary cash holdings. If indirectly affected borrowers fear worsening access and pricing of credit in the future, they should increase their cushion of cash to service their liabilities. Consistent with this idea, we find that indirectly affected non-investment grade firms maintain cash reserve buffers about 7% higher after a hurricane than the less vulnerable investment grade firms. This estimate represents an economically large relative holding of 15% compared to the unconditional sample mean.[25]

These results show that the most vulnerable indirectly affected firms reduce their investment and increase their cash reserves, which is consistent with updated expectations regarding the increased frequency and severity

[25] We note that the effects for investment grade borrowers have the opposite sign than that for non-investment grade ones. We test for joint significance of these coefficients and find that the joint effect for investment is statistically significantly different from 0 for non-investment grade firms at the 5% level, while the effect on cash holdings is not jointly statistically significant.

of future climate change disasters. Interestingly, these effects are rather large and concentrated among borrowers with the lowest access to capital. This could suggest that climate change exposure impacts not just the pricing of capital, but also its availability.

7 Conclusion

We investigate a potential channel where climate change affects corporations through the link between bank lending and climate-change related natural disasters. To overcome the simultaneity challenge when comparing direct disaster damage to updates in banks' expectations about future disasters, we estimate the reaction in loan spreads to climate-related disasters for borrowers that are at risk but not directly affected by such events. The rates that banks charge these indirectly affected borrowers increase by about 18 basis points, or 11% compared to the unconditional loan spread. These effects are strongest for borrowers who are least able to internalize a potential adverse shock, and they are more pronounced for more severe disasters. Consistent with a time-varying attention to climate change, these effects are concentrated in periods of high public attention to climate change, but short-lived.

Our findings provide the first evidence that climate change currently affects lending conditions for borrowers in the corporate lending market through the increasing severity of natural disasters. Many questions remain for future research. First and foremost is the question of whether firms and banks may shift their operations away from regions affected by climate change-related disasters to mitigate the potential medium and long term effects of climate change. Another question is how lenders should manage a long-term risk emanating from climate change in short-lived bank assets.

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Figures

Figure 1: The effect of direct exposure to climate change-related disasters on loan spreads over time
This figure presents the effect of direct exposure to climate change–related disasters on loan spreads over time. Climate change-related disasters are defined as hurricanes, wildfires and floods. Direct treatment is defined as borrowers in the top quintile of firms ranked by their operations-weighted exposure to counties directly hit by these types of disasters. Vertical lines represent 90% confidence intervals clustered by borrower and year. The years 1996 to 2001 form the base period.

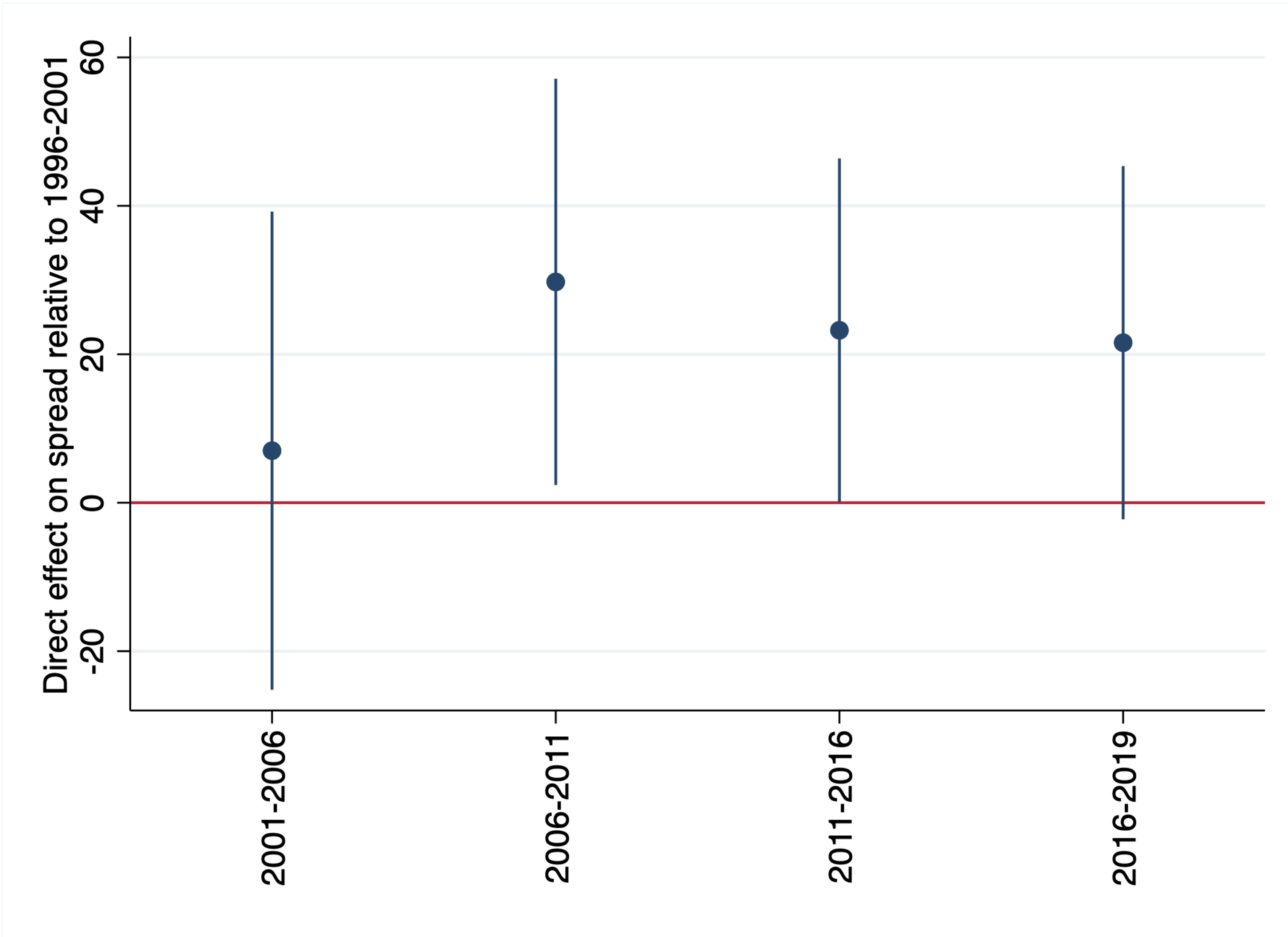


Figure 2: Geographic hurricane exposure 2008
This figure presents county level hurricane exposure in 2008 based on the total damage (in $million) caused by previous hits from SHELDUS.

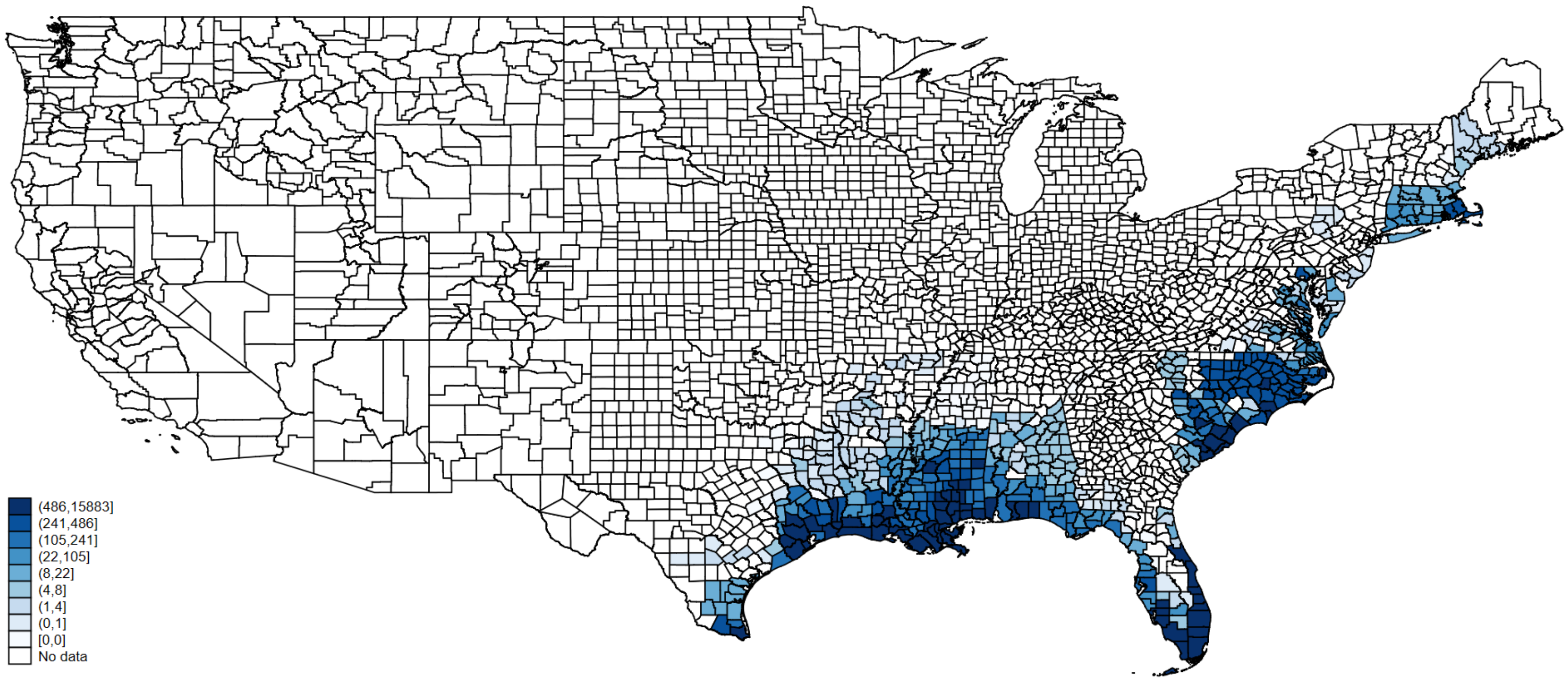


Figure 3: Geographic seismic ground motion assessment 2008
This figure presents county level earthquake exposure in 2008 based on the ground motion assessment of USGS.

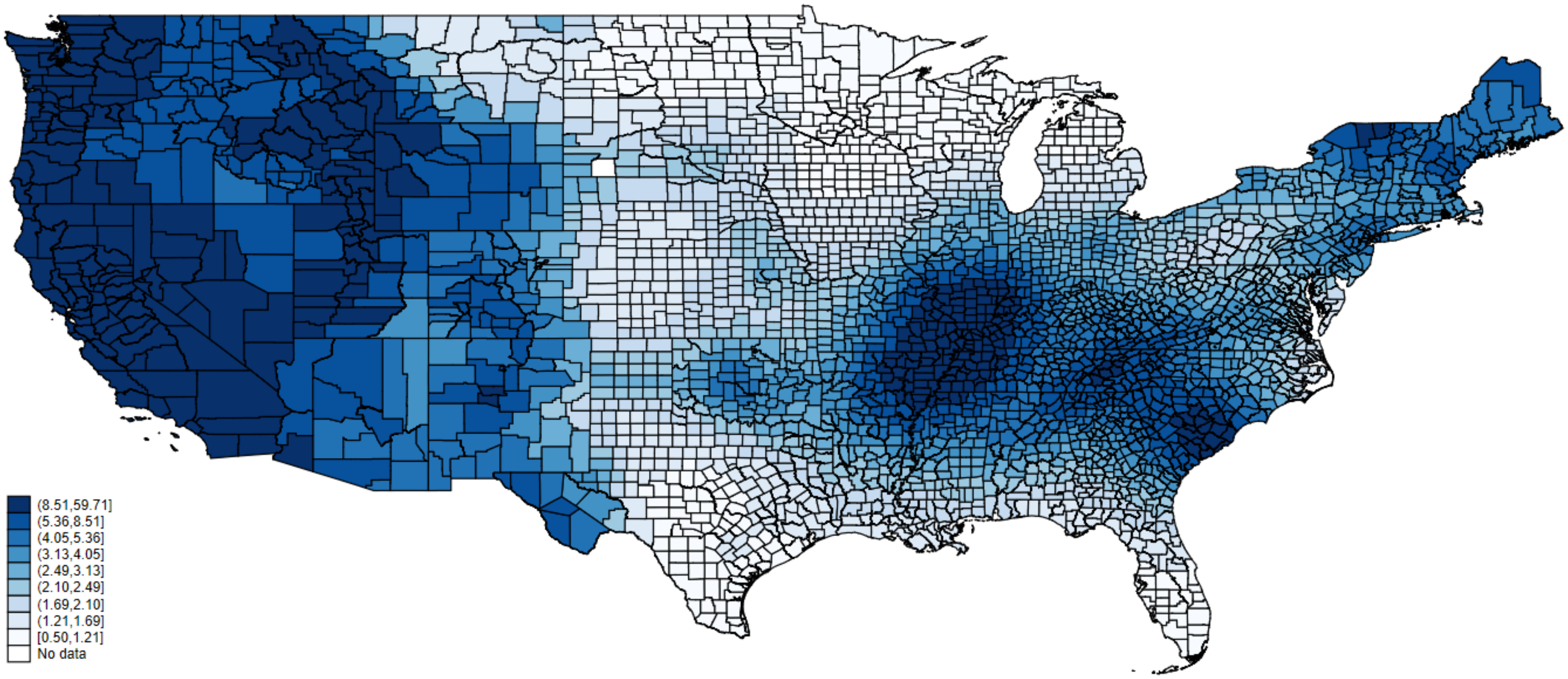
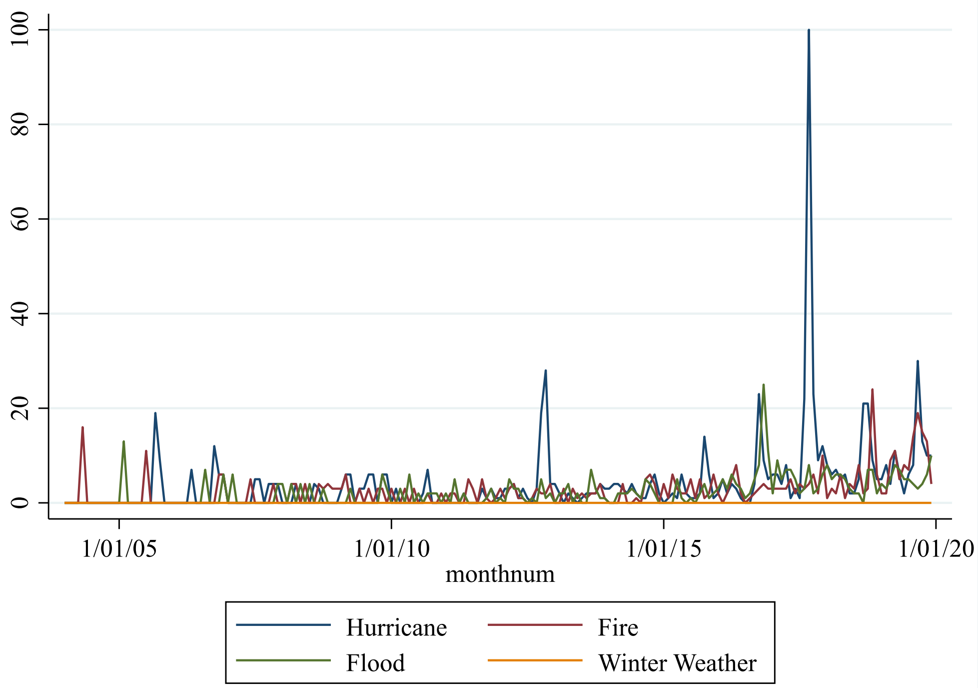


Figure 4: Search volume for climate change and natural disasters
This figure presents the time series of search volume for the combination of the search terms "climate change" and various types of disasters. Search volume is benchmarked against the highest volume, which takes a value of 100 for hurricanes in September 2017.



Tables

Table 1: Summary statistics
Panel A presents descriptive statistics for the sample of loans merged with borrower characteristics. All variables are explained in Appendix A.1. The sample contains new loan originations matched with lead lenders, excludes loans to firms that are directly affected by the major hurricane. All observations are counted by loan. Panel B reports data on property losses from natural disasters. These data are at the county level and cover natural disasters reported in SHELDUS which the Governor declared a "state of emergency" with a formal request for Federal Emergency Management Agency (FEMA) funds to respond to the disaster. The sample period of loans and natural disasters is from 1996 to 2019.

Panel A: Loan characteristics and disaster variables						
	N	Mean	Std Dev	25th	Median	75th
Spread (basis point)	21262	171.39	125.62	75.83	150.00	228.83
Maturity (year)	21262	3.98	1.87	2.92	5.00	5.00
Loan amount ($ million)	21262	1459.58	2440.00	261.60	649.73	1597.81
Financial covenant (dummy)	21262	0.58	0.49	0.00	1.00	1.00
Number of financial covenants	21262	1.25	1.31	0.00	1.00	2.00
Term loan	21262	0.22	0.36	0.00	0.00	0.42
Revolving loan	21262	0.74	0.39	0.45	1.00	1.00
Borrower total asset ($ billion)	21262	31.13	124.29	1.09	3.60	13.59
Borrower ROA	21262	0.13	0.10	0.08	0.12	0.17
Borrower debt to asset	21262	0.35	0.22	0.20	0.33	0.48
Recent hurricane	21262	0.10	0.30	0.00	0.00	0.00
Recent earthquake	21262	0.04	0.20	0.00	0.00	0.00

Panel B: Disaster Damages						
Disaster type	Number of affected counties	Total property damage across all affected counties ($B)	County property damage distribution ($M)			
			p25	p50	p75	p95
Hurricane	1912	296.19	0.17	1.45	15.94	398.07
Earthquake	16	4.34	18.77	20.17	594.41	975.55
Wildfire	556	39.13	0.05	0.77	4.51	108.33
Flooding	9247	371.12	0.05	0.36	2.00	32.50
Winter Weather	2693	14.17	0.03	0.31	2.19	24.50

Panel C: Bank internal data						
	N	Mean	Std Dev	min	p50	max
Probability of default	43008	.0114741	.0499877	.0	0.0025	1

Table 2: Interest rate spreads and climate change-related disasters
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	17.274**	18.751**	19.158**	18.778**
	(7.717)	(8.371)	(8.621)	(8.488)
Indirect hurricane	3.016	3.118	3.538	3.467
	(5.041)	(4.399)	(4.026)	(3.973)
Recent hurricane	3.419	0.501	0.857	1.178
	(3.790)	(3.712)	(3.551)	(3.556)
N	21262	21262	21262	21262
R^2	0.696	0.730	0.741	0.742
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

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Table 3: Interest rate spreads and non-climate change-related disasters

This table reports regressions of loan spread (in basis points) on borrowers' indirect earthquake exposure indicator with the occurrence of a major earthquake in the preceding 3 months. The indirect earthquake exposure is constructed based on each firm's location-weighted USGS's seismic hazard ground motion assessment maps. The sample excludes loans to firms that are directly affected by the major earthquake. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-earthquake disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect earthquake × *Recent earthquake*	-15.058	-7.162	-9.869	-9.740
	(9.257)	(9.693)	(8.738)	(12.442)
Indirect earthquake	-1.811	-0.027	-1.550	-1.172
	(5.329)	(4.731)	(4.288)	(3.957)
Recent earthquake	11.164	7.910	8.024	7.971
	(10.584)	(8.407)	(7.747)	(6.426)
N	19759	19759	19759	19759
R^2	0.702	0.738	0.750	0.751
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table 4: Pricing of climate change-related disasters across borrowers

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. *Market leverage* and *Tangibility* are normalized values of firms' market leverage ratio and tangibility of assets, respectively. *Non-investment grade* is an indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB). The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1)	(2)	(3)
Indirect hurricane × *Recent hurricane*	17.538*	15.877*	7.114
	(8.888)	(8.003)	(9.292)
Indirect hurricane × *Recent hurricane* × *Market leverage*	25.262*		
	(14.684)		
Indirect hurricane × *Recent hurricane* × *Tangibility*		14.477*	
		(8.028)	
Indirect hurricane × *Recent hurricane*× *Non-investment grade*			45.984*
			(23.960)
N	20269	20616	19658
R^2	0.746	0.741	0.753
Bank × Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Other interactions	Yes	Yes	Yes

Table 5: Pricing of climate change-related disasters by size of the event

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. $Recent\ hurricane_{>\$100bn}$ indicates the hurricanes with total losses exceeding \$100 billion, $Recent\ hurricane_{other}$ indicates the rest of major hurricanes. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1)	(2)	(3)
$Indirect\ hurricane \times Recent\ hurricane_{>\$100bn}$	31.022*		34.059**
	(15.993)		(15.817)
$Indirect\ hurricane \times Recent\ hurricane_{other}$		16.136**	16.671**
		(7.692)	(7.707)
Indirect hurricane	4.292*	3.859*	3.514
	(2.288)	(2.334)	(2.323)
$Recent\ hurricane_{>\$100bn}$	-0.390		-1.151
	(4.453)		(4.483)
$Recent\ hurricane_{other}$		1.355	1.094
		(2.274)	(2.285)
N	21262	21262	21262
R^2	0.742	0.742	0.741
Bank× Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table 6: Pricing of climate change-related disasters in the secondary market
This table reports regressions of the log of weekly average quote price in the loan secondary market on borrowers' indirect hurricane risk indicator with the occurrence of hurricanes in the preceding four weeks. The sample includes existing loans' weekly quotes in 12 weeks before or after a hurricane hit, but excludes loans to firms that are directly affected by a major hurricane. Standard errors clustered by loan reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Log Average Quote			
	(1)	(2)	(3)	(4)
Indirect hurricane $\times$ *Recent hurricane*	-0.032*	-0.024***	-0.033**	-0.021***
	(0.017)	(0.008)	(0.016)	(0.008)
Indirect hurricane	-0.015	-0.040**	-0.024	-0.055***
	(0.020)	(0.016)	(0.020)	(0.017)
Recent hurricane	-0.000	0.007**	0.008**	0.010***
	(0.004)	(0.003)	(0.004)	(0.003)
N	62085	62085	62085	62085
R^2	0.003	0.850	0.043	0.858
Loan FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Table 7: Banks' internal assessment of climate change

This table reports regressions of banks' assessments of default probabilities on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. The sample excludes default probabilities of firms directly affected by a major hurricane. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, the book to market ratio, and borrower's direct exposure to non-hurricane disasters, if any. The first four controls are lagged by four periods. The sum of coefficients captures the sum and significance of the coefficient on the interaction term between the *Indirect hurricane* indicator and the indicator capturing whether there was a recent hurricane. Standard errors double clustered by firm and date reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Probability of default over time		
	(1)	(2)	(3)
Indirect hurricane × *Recent hurricane_this quarter*	0.011**	0.008*	0.007
	(0.005)	(0.004)	(0.005)
Indirect hurricane × *Recent hurricane_1 quarter prior*			0.003
			(0.005)
Indirect hurricane × *Recent hurricane_2 quarters prior*			0.003
			(0.004)
N	43008	43008	39458
R^2	0.355	0.375	0.374
Bank × Year–Quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Firm controls	No	Yes	Yes
Sum of coefficients			0.012*

Table 8: Bank disaster exposures and interest rate spreads
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. *Bank disaster exposure* is the ratio of a bank's outstanding loans assigned to disaster firms, measured either by loan amount or loan incidence. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	17.481**	14.344*	17.546**	14.373*
	(7.941)	(7.855)	(7.945)	(7.852)
Indirect hurricane	0.428	1.264	0.454	1.276
	(3.233)	(2.693)	(3.237)	(2.694)
Recent hurricane	1.237	-1.375	1.040	-1.459
	(2.905)	(2.859)	(2.926)	(2.911)
Bank disaster exposure (*loan incidence*)	3.294**	1.532		
	(1.632)	(1.508)		
Bank disaster exposure (*loan amount*)			2.833**	1.310
			(1.259)	(1.261)
N	16723	16723	16723	16723
R^2	0.731	0.775	0.731	0.775
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	Yes	No	Yes

Table 9: Economic links between borrowers and interest rate spreads
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. *Customer disaster exposure* and *Supplier disaster exposure* are a borrower's exposure through its customers and suppliers to natural disasters, respectively. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
Indirect hurricane × Recent hurricane	17.086**	14.222*	17.134**	14.294*	17.271**	14.422*
	(7.835)	(7.843)	(7.755)	(7.800)	(7.763)	(7.818)
Indirect hurricane	0.513	1.320	0.593	1.407	0.624	1.437
	(3.230)	(2.695)	(3.206)	(2.679)	(3.218)	(2.686)
Recent hurricane	3.145	-0.596	3.505	-0.249	3.282	-0.458
	(2.928)	(2.911)	(2.903)	(2.875)	(2.935)	(2.901)
Customer disaster exposure	16.056	15.164			15.723	14.766
	(13.105)	(12.620)			(13.141)	(12.647)
Supplier disaster exposure			-31.775**	-33.739**	-31.697**	-33.657**
			(15.641)	(14.756)	(15.664)	(14.772)
N	16723	16723	16723	16723	16723	16723
R^2	0.731	0.775	0.731	0.775	0.731	0.775
Bank× Year Hurricane FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes

Table 10: Time-varying attention to climate change

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. *WSJ index* is the standardized attention index constructed in Engle et al. (2021) in the month when a loan is issued, lagged by one quarter. *Above median attention*, *medium tercile attention*, and *top tercile attention* are indicators for loans issued in months with above median, medium tercile, and highest tercile attention to climate change measured by the index, lagged by one quarter. The sample excludes loans to firms that are directly affected by major hurricanes. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1)	(2)	(3)
Indirect hurricane × *recent hurricane*	16.603*	-13.047	-44.620***
	(8.360)	(13.647)	(14.984)
Indirect hurricane × *recent hurricane* × *WSJ index*	41.659**		
	(17.006)		
Indirect hurricane × *recent hurricane* × *above median attention*		47.982**	
		(17.392)	
Indirect hurricane × *recent hurricane* × *medium tercile attention*			66.370***
			(18.420)
Indirect hurricane × *recent hurricane* × *top tercile attention*			83.067***
			(25.388)
N	19375	19375	19375
R^2	0.754	0.754	0.754
Bank× Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table 11: Relative time effects

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and quarter reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × Future hurricane_2 quarters future	2.214	2.468	2.122	2.528
	(6.928)	(6.822)	(6.450)	(6.418)
Indirect hurricane × Future hurricane_1 quarters future	5.333	4.117	5.122	4.014
	(6.526)	(6.164)	(6.090)	(5.808)
Indirect hurricane × Recent hurricane_This quarter	17.783*	18.553*	19.010*	19.632*
	(9.893)	(10.816)	(9.905)	(10.723)
Indirect hurricane × Recent hurricane_1 quarter prior	-0.972	0.472	-2.627	-1.027
	(9.064)	(8.814)	(7.793)	(7.796)
Indirect hurricane × Recent hurricane_2 quarter prior	-4.784	-4.528	-2.827	-2.661
	(7.454)	(7.903)	(7.051)	(7.539)
N	21262	21262	21262	21262
R^2	0.696	0.730	0.713	0.742
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table 12: Indirect hits and future severe weather damage

This table reports regressions of firms' future direct hurricane hits on their previous indirect hurricane exposure, defined as the number of previous instances in which they were indirectly affected. The outcome in column 1 is *Direct hit*, an indicator of whether a firm suffered direct hurricane damage in a given month. The outcome in column 2 is *Direct hit large*, an indicator of whether a firm suffered direct hurricane damage in the top quintile relative to all other firms in a given month. The outcome in column 3 is *Direct hit cont.*, the direct disaster quintile in continuous fashion. Standard errors double clustered by firm and year-month reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Direct hit	Direct hit large	Direct hit cont.
	(1)	(2)	(3)
Previous indirect hit	0.023***	0.024***	0.094***
	(0.004)	(0.004)	(0.018)
Indirect hurricane	0.026***	0.032***	0.109***
	(0.005)	(0.006)	(0.021)
N	557437	557437	557437
R^2	0.361	0.210	0.333
Firm FE	Yes	Yes	Yes
Year month FE	Yes	Yes	Yes

Table 13: Corporate finance effects of climate change risk

This table reports regressions of firms' annual investment ratio and cash ratio on their indirect hurricane exposure indicator with the occurrence of a major hurricane in the previous quarter. $Non-investment\ grade$ is an indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB). The sample excludes firm-years that are directly affected by hurricanes. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls one quarter lagged variables including log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	CapEx/Assets (%)		Cash/Liabilities (%)	
	(1)	(2)	(3)	(4)
$Indirect\ hurricane \times Recent\ hurricane$	0.233	0.304	-5.344	-5.708
	(0.199)	(0.213)	(3.340)	(3.336)
$Indirect\ hurricane \times recent\ hurricane \times non-investment\ grade$		-0.851***		7.233**
		(0.298)		(3.370)
N	21613	21613	21786	21614
R^2	0.675	0.675	0.578	0.633
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

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Internet Appendix for
"The rising tide lifts some interest rates: climate change, natural disasters, and loan pricing"

A.1 Variable Definitions

Loan Variables	
Spread	The all-in-drawn spread in basis points
Loan amount	Loan amount in dollars, adjusted to 2019 values
Maturity (Years)	The number of years between loan start and end dates
Term loan	Indicator equal to one if the loan type is term loan
Revolving loan	Indicator equal to one if the loan type is revolver
Financial covenant (indicator)	Indicator equal to one if the loan contract includes covenants
Number of financial covenants	The number of covenants in a loan contract
Disaster Variables	
$Indirect\ hurricane_{i,t}$	Indicator equal to one if firm i is in the top quintile when we rank firms in month t by their location-weighted exposure to hurricanes. The exposure is based on a firm's total footprints in hurricane-prone counties. A hurricane-prone county in month t is the one which, in the past 10 years, exceeds 90% of other counties nationwide in terms of disaster losses caused by hurricanes.
$Indirect\ earthquake_{i,t}$	Indicator equal to one if firm i is in the top quintile when we rank firms in month t by their location-weighted ground motion assessment. Each location's ground motion assessment is its most recent assessment of the potential for earthquake ground shaking by the U.S. Geological Survey for the Department of the Interior.
$Recent\ hurricane_t$	A time indicator equal to one if a hurricane hit during the preceding 3 months.
$Recent\ earthquake_t$	A time indicator equal to one if an earthquake hit during the preceding 3 months.
Other Variables	
CapEx/Assets	Borrower physical capital expenditure (PP&E) over assets.
Cash/Liabilities	Borrower cash divided by current liabilities.
Market leverage	The normalized value of firms' market leverage ratio.

Previous indirect hit	Number of quarters in the past during which a company was at-risk and a disaster happened.
ROA	Borrower return on asset calcualted as net profits over total assets.
Tangibility	The normalized value of firms' tangibility of assets.
Total assets	Borrower total assets in USD bn.
$Non-investment\ grade$	Indicator equal to 1 for firms with a senior unsecured credit rating below investment grade (BBB) in S&P ratings.
$WSJindex$	The Wall Street Journal climate change news index, a standardized attention index constructed in Engle et al. (2021).
$Bank\ disaster\ exposure_{m,t}$	Bank m's exposure to natural disasters that occur during the preceding 3 months. It is the ratio of the bank's outstanding loans, when a disaster occurs, that are assigned to disaster firms, measured either by loan amount or loan incidence.
$Customer\ disaster\ exposure_{i,t}$	Firm i's exposure through customers to natural disasters that occur during the preceding 3 months. It is the ratio of sales to disaster customers to the firm's total sales in the same quarter.
$Supplier\ disaster\ exposure_{i,t}$	Firm i's exposure through suppliers to natural disasters that occur during the preceding 3 months. It is the ratio of the sales from disaster suppliers to those suppliers' total sales in the same quarter.

A.2 Anecdotal evidence

This section provides anecdotal evidence that the link between climate change, natural disasters and credit risk is well understood for financial market participants and impacts banks' lending decisions. We hand-collect evidence from the 2010 and 2019 10-K filings of 10 major U.S. banks (by assets). We present an overview of this analysis in Appendix Table A.1. As a first pass, we report whether the 10-K explicitly mentions climate change and natural disasters (or severe weather) in close proximity. Out of the 10 banks, all explicitly mention these two topics in 2019. Next, we look for any mentioning of a link between increasing severity and frequency of these disasters and climate change. All banks except Morgan Stanley and Wells Fargo explicitly state that there is a potential link between climate change and worsening severe weather incidents in 2019. Interestingly, already in 2010, seven of the 10 banks already mention a link between climate change and natural disasters, although only 4 explicitly mention an increasing trend.

In the last column of Appendix Table A.1, we report specific natural disasters mentioned in the context of climate change. Four banks mention specific disasters, with all of them mentioning hurricanes and/or storms. In addition, both Bank of America and JP Morgan Chase reference the risk of wild fires, and JP Morgan Chase mentions floods. In 2010, the only bank mentioning a specific disaster is SunTrust, which mentions hurricanes.

These results show that banks widely consider a link between climate change and natural disasters. In addition, the specific mentioning of hurricanes, wildfires and floods reassures our selection of climate change disasters. Below we present a selection of specific quotes from these 10-K filings, as well as other industry documents, that corroborate the attention to climate change disasters for credit market participants. These excerpts show that lenders incorporate climate change induced disaster risk into their lending decisions. **Bold text** presents particularly relevant statements highlighted by us.

1. Quotes from JPMorgan Chase 2019 10-K:
   "JPMorgan Chase operates in many regions, countries and communities around the world where its businesses, and the activities of its clients and customers, could be disrupted by climate change. Potential physical risks from climate change may include:
   - altered distribution and intensity of rainfall
   - prolonged droughts or flooding
   - increased frequency of wildfires
   - rising sea levels
   - rising heat index

   These climate driven changes could have a material adverse impact on asset values and the financial performance of JPMorgan Chase's businesses, and those of its clients and customers."

2. Quotes from Bank of America's 2018 carbon disclosure project report:
   " There is scientific consensus that flood risks are increasing in many regions due to climate change. [...] **We conduct an annual assessment of physical risks to our facilities from factors including severe weather, wildfires and flooding.**"

3. Quotes from Citi's 2019 10-K:
   "**Climate change presents immediate and long-term risks to Citi and to its clients and customers, with the risks potentially increasing over time.** Climate risk can arise from physical risks (risks related to the physical effects of climate change) [...] **Citi's Environmental and Social Risk Management Policy incorporates climate risk assessment for credit underwriting purposes.**"

4. Quotes from Goldman Sachs' 2019 10-K:
"Climate change may cause extreme weather events that disrupt operations at one or more of our primary locations, which may negatively affect our ability to service and interact with our clients, and also may adversely affect the value of our investments, including our real estate investments. **Climate change may also have a negative impact on the financial condition of our clients, which may decrease revenues from those clients and increase the credit risk associated with loans** and other credit exposures to those clients."

5. Quotes from U.S. Bancorp' 2019 10-K:
"[...] **the force and frequency of natural disasters are increasing as the climate changes.**"

6. Quotes from Truist's 2018 10-K:
"[BB&T's operations and customers] could be adversely impacted by such events in those regions, **the nature and severity of which may be impacted by climate change** and are difficult to predict. These and other unpredictable natural disasters could have an adverse effect on BB&T in that such events could materially disrupt its operations or the ability or willingness of its customers to access the financial services offered by BB&T"

7. Quotes from PNC's 2019 10-K:
"Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] **we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans.**"

8. Quotes from TD Bank's 2019 10-K:
"Climate change risk has emerged as one of the top environmental risks for the Bank as extreme weather events, shifts in climate norms, and the global transition to a low carbon economy risks increase and evolve."

9. Quotes from Deutsche Bank's 2018 White Paper on Climate Change:
"We believe investors have no place to hide when it comes to the effects of physical climate change since even if emissions were cut to zero tomorrow, **society will still face intensifying extreme weather events over the next several decades.** [...] **Perhaps the most telling metric of a company's climate risk is the location of its assets and their exposure to changing extreme weather patterns. The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks. [...] Financial risk can go beyond recovering from an extreme weather event. Even a company that was not directly affected might be financially impacted. For example, through a gradual increase in its operational expenses due to rising insurance costs, a default in bank loans or other debt, or at a more macro-level, lower consumption levels.**"

Lenders are not the only market participants that connect climate change to severe weather and credit risk. Both Standard and Poor's as well as Moody's Investor Services have released documents detailing their pricing of climate change induced severe weather:

1. Quotes from Standard and Poor's 2017 climate change report:
"We know that **climate change will increase the incidence and severity of weather events, both chronic and acute, such as hurricanes and droughts.** [..] Severe weather conditions lead to flooding

of a large part of the construction site at the end of December 2015 and beginning of January 2016. [...] On Feb. 14, 2017, we lowered the Aberdeen Roads (Finance) plc rating to 'BBB+' from 'A-' [...]"

2. Quotes from Moody's 2020 research note on U.S. utilities:
   "As **climate change increases the frequency and severity of extreme weather events, anticipation of these hazards will be increasingly reflected in the capital investment programs of utilities.**"
3. Quotes from Moody's 2017 research note on U.S. state and local government bonds:
   "The report differentiates between climate trends, which are a longer-term shift in the climate over several decades, versus **climate shock, defined as extreme weather events like natural disasters, floods, and droughts which are exacerbated by climate trends.** Our credit analysis considers the effects of climate change when we believe a meaningful credit impact is highly likely to occur and not be mitigated by issuer actions, even if this is a number of years in the future."

Quotes from United States Fourth National Climate Assessment:

1. "The National Oceanic and Atmospheric Administration estimates that **the United States has experienced 44 billion-dollar weather and climate disasters since 2015** (through April 6, 2018), incurring costs of nearly $400 billion."
2. **"Since 1980, the number of extreme weather-related events per year costing the American people more than one billion dollars per event has increased significantly (accounting for inflation), and the total cost of these extreme events for the United States has exceeded $1.1 trillion."**
3. The report specifically mentions hurricanes, floods, droughts and wildfires, as well as tornadoes and heat waves

On an international level, the United Nations Environment Programme Finance Initiative (UNEP FI) addresses the issue:

1. Quotes from United Nations Environment Programme Finance Initiative 2018 Navigating a New Climate Report:
   "**To date, risks and opportunities resulting from the physical impacts of climate change (due to more frequent and extreme weather and climate events, and gradual shifts in climate patterns) have received attention within the insurance sector, but have not been widely assessed in credit and lending portfolios held by banks.** [...] Extreme events represent acute climate variability and may only occur in specific locations, such as floodplains or tropical cyclone regions. **The extreme events covered in the methodologies are: cyclone, flood, wildfire, drought and extreme heat.**"

A.3 Evidence on disasters and climate change

A key assumption in our paper is that certain disasters have experienced an increase in severity and frequency, while others have not. In this section, we provide a detailed discussion about why we classify these disasters the way we do, and provide evidence from climate scientists on the actual developments for these disasters, as well as evidence on the thoughts of market participants that ultimately price these disasters.

A The state of climate science evidence linking disasters and climate change

We begin by reviewing the evidence on the severity and frequency of certain natural disasters. The scientific view on natural disasters and their connection to climate change has changed drastically in the recent decade. We mostly rely on the aggregation of evidence presented in the most recent National Oceanic and Atmospheric Administration's (NOAA) climate special report (Wuebbles, Fahey, Hibbard, Arnold, DeAngelo, Doherty, Easterling, Edmonds, Edmonds, Hall, et al., 2017) to survey the vast literature on climate change and natural disasters in the United States.

There is a strong distinction between the trends affecting north Atlantic hurricanes threatening the US on the one hand, and the global tropical storm (Cyclone) activity on the other. Outdated models predicted declines in hurricanes globally, but these models were missing geographically heterogeneous patterns. A new generation of models predicts **global** fall in cyclones, but an increase in intense north Atlantic hurricanes (Bender, Knutson, Tuleya, Sirutis, Vecchi, Garner, and Held, 2010). While evidence is mixed for an increasing trend in the severity (or damages) of hurricanes over much of the early 20th century, there is a distinct trend towards more intense and severe hurricanes in recent decades (Grinsted, Ditlevsen, and Christensen, 2019; Smith and Katz, 2013). Though some uncertainty about the precise degree to which climate change impacts these trends (for an early debate between these viewpoints see for example Elsner, Jagger, et al. (2009)), the overall evidence in the last 20 years clearly shows an increasing threat from hurricanes.

Wuebbles et al. (2017) summarizes the state of the literature on hurricanes, wildfires, and floods, as such:

For hurricanes:

"**For Atlantic and eastern North Pacific hurricanes and western North Pacific typhoons, increases are projected in precipitation rates (high confidence) and intensity (medium confidence). The frequency of the most intense of these storms is projected to increase in the Atlantic and western North Pacific (low confidence) and in the eastern North Pacific (medium confidence)**".

For floods:

"**Recent analysis of annual maximum stream- flow shows statistically significant trends in the upper Mississippi River valley (increasing) and in the Northwest (decreasing). In fact, across the midwestern United States, statistically significant increases in flooding are well documented. These increases in flood risk and severity are not attributed to 20th century changes in agricultural practices but instead are attributed mostly to the observed increases in precipitation. [... The main conclusion] states that the frequency and intensity of heavy precipitation events are projected to continue to increase over the 21st century with high confidence. Given the connection between extreme precipitation and flooding, and the complexities of other relevant factors, we concur with the IPCC Special Report on Extremes (SREX) assessment of "medium confidence (based on physical reasoning) that projected increases in heavy rainfall would contribute to increases in local flooding in some catchments or regions**".

The evidence on wild fires comes to a similar conclusion:

"**The incidence of large forest fires in the western United States and Alaska has increased since the early 1980s (high confidence) and is projected to further increase in those regions as the climate warms, with profound changes to certain ecosystems (medium confidence). [...] Nonetheless, there is medium confidence for a human-caused climate change contribution to increased forest fire activity in Alaska in recent decades with a likely further increase as the climate continues to warm, and low to medium confidence for a detectable human climate change contribution in the western United States based on existing studies. Recent literature does not contain a complete robust detection and attribution analysis of forest fires including estimates of natural decadal and multidecadal variability, as described in Chapter 3: Detection and Attribution, nor separate the contributions to observed trends from climate change and forest management**".

Overall, the scientific evidence strongly points towards a relationship between climate change and an increasing severity and frequency of north Atlantic hurricanes, wildfires, and floods.

Next, we turn towards winter weather. We argue that there is substantial uncertainty about the relationship between climate change and winter weather, with no evidence of an increase in severity or frequency. Therefore, winter weather can act as a plausible placebo test in our analysis. The evidence from climate scientists supports this notion. Wuebbles et al. (2017) summarize the inconclusive state of the evidence as follows:

"**In general, winter is warming faster than summer (especially in northern latitudes). [...] Winter storm tracks have shifted slightly northward (by about 0.4 degrees latitude) in recent decades over the Northern Hemisphere. More generally, extratropical cyclone activity is projected to change in complex ways under future climate scenarios, with increases in some regions and seasons and decreases in others. There are large model-to-model differences among CMIP5 climate models, with some models underestimating the current cyclone track density. Enhanced arctic warming (arctic amplification), due in part to sea ice loss, reduces lower tropospheric meridional temperature gradients, diminishing baroclinicity (a measure of how misaligned the gradient of pressure is from the gradient of air density)—an important energy source for extratropical cyclones. At the same time, upper-level meridional temperature gradients will increase due to a warming tropical upper troposphere and a cooling high-latitude lower stratosphere. While these two effects counteract each other with respect to a projected change in midlatitude storm tracks, the simulations indicate that the magnitude of arctic amplification may modulate some aspects (e.g., jet stream position, wave extent, and blocking frequency) of the circulation in the North Atlantic region in some seasons**".

Another type of severe weather we potentially considered was tornadoes. However, it is highly unclear how climate change is impacting the current and future severity of tornadoes (Gensini and Brooks, 2018). The climate assessment states that

"**Inferring current changes in tornado activity is hampered by changes in reporting standards, and trends remain highly uncertain.**

This general uncertainty is compounded by the fact that tornadoes often spawn from hurricanes. For example, hurricane Harvey in 2017 spawned no less than 52 Tornadoes. As a result, tornadoes often hit areas contemporaneously with hurricanes and it is not possible to slate tornado damage from the damage caused by the hurricane that spawned these tornadoes. We therefore focus our analysis on the disasters that are clearer cuts in their relationship to climate change.

B The perception of market participants linking disasters and climate change

Ultimately, what matters more than the scientific consensus is the belief of market participants who set prices. If market participants decide to price increased severity and frequency of hurricanes in loans, this will be reflected in our data irrespective of the actual climate science evidence.

We therefore collect anecdotal evidence on whether market participants believe that there is a connection between climate change and specific disasters. First, Appendix Table A.1 shows that banks mention specific disasters as connected to climate change. We find that four banks mention hurricanes or storms, two mention wildfires, and there is one mention of heat and flooding, respectively. Therefore, all disasters we classify as related to climate change are mentioned. On the other hand, no bank mentions a connection between winter weather and climate change, although the storms mentioned by two could theoretically include winter storms.

As a next check, we turn to the attention of the general public to climate change and natural disasters. We obtain data from google trends spanning 2004 to 2020, and compare searches that connect climate change to different natural disasters. Specifically, we compare the following search terms for the United States:

"climate change" & "hurricane", *"climate change" & "fire"*, *"climate change" & "flood"*, and *"climate change" & "winter weather"*. Search interest is benchmarked relative to the maximum search interest during our sample, which is a value of 100 for *"climate change" "hurricane"* in September 2017. We find that there is a general trend towards higher attention for all climate change related disasters during our sample period. However, we note that there are substantial spikes in interest of at least 15% for all climate change related disasters at least once in the earlier stages of the search data sample. Searches for climate change and winter weather never reach 1% of the volume of the maximum searches for climate change and hurricanes. The average monthly attention index to hurricanes and climate change is 4.6, compared with 2.52 for fires, and 2.25 for floods. The search interest for floods and fires is therefore almost an average of 50% of that for hurricanes. The search volume for winter weather never reaches 1%. In additional analysis, we test for attention to alternative words for winter weather. The only phrase that ever exceeds 1% of search volume for hurricanes is *"climate change" "winter storms"*. The average attention to this phrase is 0.08, less than 2% of the average volume for hurricanes and barely 3% the volume fore fires and floods.

We therefore conclude that the general public, and hence by extension likely market participants, pay substantial attention to the link between climate change and hurricanes, fires, and floods. There is no evidence of attention to climate change increasing the severity of winter weather.[26]

[26]In separate results, as an alternative comparison, we compare (*"climate change" "hurricanes"*) to (*"climate change" "winter storm"*). We find that the aggregate search interest for winter storms is only 1.8% of that for hurricanes during 2004 to 2020, with the maximum search interest for winter storms never exceeding 2% of the maximum search interest for hurricanes. Throughout the sample, (*"climate change" "winter storm"*) has zero search interest until November 2011. We never find any search interest for (*"climate change" "winter weather"*) or (*"climate change" "blizzard"*).

A.4 Appendix Tables

Table A.1: Climate change related disasters in banks' 10-K filings
This table reports a summary of the degree to which the 10 largest U.S. banks by assets mention climate change in their 2019 annual reports. The column "climate disasters" reports if these filings mention severe weather or natural disasters in the context of climate change broadly. The second column, "worsening trend" reports if the filings mention a potential increase in severity of these disasters due to climate change. The final column, "specific disasters", reports which specific types of severe weather are mentioned in this context, if any.

Panel A: 2019

Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	Yes	Yes	Flooding, wildfire, heat, storm
Bank of America	Yes	Yes	Fire, hurricanes
Citi	Yes	Yes	None
Wells Fargo	Yes	No	Hurricanes
Goldman Sachs	Yes	Yes	None
Morgan Stanley	Yes	No	None
U.S. Bankcorp	Yes	Yes	None
Truist	Yes	Yes	Hurricanes, storms
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

Panel B: 2010

Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	No	No	None
Bank of America	No	No	None
Citi	No	No	None
Wells Fargo	Yes	No	None
Goldman Sachs	Yes	No	None
Morgan Stanley	Yes	No	None
U.S. Bankcorp	Yes	Yes	None
Truist (Suntrust)	Yes	Yes	Hurricanes
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

Table A.2: Pricing of climate change-related disasters by size of the event (climate aggregated)
This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster indicator with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1)	(2)	(3)
Indirect disasters × *Recent disasters_50mil*	2.829		
	(2.410)		
Indirect disasters × *Recent disasters_100mil*		5.721**	
		(2.542)	
Indirect disasters × *Recent disasters_200mil*			8.571***
			(2.717)
Indirect disasters	-2.251	-2.786	-3.140
	(2.146)	(2.183)	(2.195)
N	21127	21127	21127
R^2	0.774	0.774	0.775
Bank × Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan Controls	No	Yes	No
Firm Controls	No	No	Yes

Table A.3: Robustness: Alternative measures of earthquake exposure and rates

This table reports regressions of loan spread (in basis points) on different indirect earthquake exposure and earthquake occurrence indicator. *Indirect earthquake* is defined as geological exposure based on each firm's location-weighted USGS's seismic hazard ground motion assessment, as in Table 3. The indicator *Recent earthquake* is also defined as in Table 3 as a recent earthquake in the United States. *Indirect earthquake hit* measures the indirect earthquake exposure based on a firm's total footprint in counties that have *historical* earthquake hit records. *Recent earthquake abroad* is an indicator of the occurrence of one of the ten most serious global earthquakes since 2000, as well as three major earthquakes from 1996 to 2000. The sample excludes loans to firms that are directly affected by the major domestic earthquake. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1)	(2)	(3)
Indirect earthquake × *Recent earthquake abroad*	-3.303		
	(7.707)		
Indirect earthquake hit × *Recent earthquake*		-18.363	
		(16.032)	
Indirect earthquake hit × *Recent earthquake abroad*			0.946
			(5.248)
Indirect earthquake	0.084		
	(4.034)		
Indirect earthquake hit		-3.835	-4.659
		(4.003)	(4.589)
Recent earthquake		9.473	
		(6.272)	
Recent earthquake abroad	1.562		0.176
	(4.752)		(3.646)
N	19759	24042	24042
R^2	0.751	0.735	0.735
Bank×$Year\ FE$	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table A.4: Robustness: Rates and non-climate change related disasters: no 10-year window

This table reports regressions of loan spread on borrowers' indirect earthquake exposure indicator with the occurrence of a major earthquake in the preceding 3 months. Unlike in the main specification, where we measure earthquake exposure using a 10-year rolling window, we utilize the complete disaster history to measure earthquake exposure in these tests. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) non-climate change disasters				
	Spread			
	(1)	(2)	(3)	(4)
Indirect earthquake × *Recent earthquake*	-27.426***	-24.185***	-22.121***	-21.945***
	(7.747)	(8.113)	(6.570)	(6.547)
Indirect earthquake	-6.339	-4.189	-1.843	-1.309
	(5.666)	(5.667)	(5.544)	(5.563)
Recent earthquake	13.463	11.799	11.685	11.593
	(10.759)	(8.343)	(7.159)	(7.067)
N	24042	24042	24042	24042
R^2	0.686	0.722	0.734	0.735
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table A.5: Robustness: Climate change and non-climate change disasters jointly
This table reports regressions of loan spread (in basis points) on borrowers' indirect natural disaster indicators with the occurrence of the same type of disasters. Both climate and non-climate change related disasters are included, defined as hurricanes and earthquakes, respectively. The indirect earthquake exposure is either measured by each firm's location-weighted ground motion assessment (as in Table 3) or total footprints in counties that have historical earthquake hit records (as in Table A.3) . The sample excludes loans to firms that are directly affected by those disasters. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane or non-earthquake disasters if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread	
	(1)	(2)
	ground motion assessment	historical earthquake records
Indirect hurricane × Recent hurricane	19.172*	18.733**
	(10.149)	(8.616)
Indirect earthquake × Recent earthquake	-10.501	-16.187
	(10.479)	(10.655)
Indirect hurricane	2.605	3.971
	(4.619)	(3.967)
Indirect earthquake	-0.839	-6.639
	(3.993)	(4.158)
Recent hurricane	2.928	1.411
	(5.088)	(3.552)
Recent earthquake	7.028	8.242
	(7.140)	(7.845)
N	17480	21057
R^2	0.758	0.742
Bank× Year FE	Yes	Yes
Firm FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes

Table A.6: Robustness: Exclude hurricane season

This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster indicator with the occurrence of the same type of disasters. Climate change related disasters include hurricanes. We define the months of June through November as hurricane season, and exclude all loans taken out during these times. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	78.400***	69.840**	71.938**	64.442**
	(25.960)	(27.541)	(27.401)	(28.387)
Indirect hurricane	4.447	3.087	3.942	2.916
	(7.763)	(7.514)	(6.754)	(6.710)
Recent hurricane	-7.945	-9.299	-5.351	-7.162
	(9.202)	(8.622)	(8.891)	(8.299)
N	10307	10307	10307	10307
R^2	0.745	0.771	0.760	0.782
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.7: Flooding and rates

This table reports regressions of loan spread (in basis points) on borrowers' indirect flooding exposure indicator with the occurrence of a major flood in the preceding 3 months. The sample excludes loans to firms that are directly affected by the major flood. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-flooding disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect flooding × *Recent flooding*	10.981**	10.572**	10.336**	10.070**
	(4.883)	(4.748)	(4.413)	(4.300)
Indirect flooding	-0.485	-0.283	-0.321	-0.198
	(4.535)	(4.455)	(4.341)	(4.282)
Recent flooding	-7.907**	-7.936**	-7.635**	-7.646**
	(3.098)	(3.109)	(3.306)	(3.342)
N	20285	20285	20285	20285
R^2	0.754	0.754	0.769	0.769
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table A.8: Wildfires and rates

This table reports regressions of loan spread (in basis points) on borrowers' indirect wildfire exposure indicator with the occurrence of a major wildfire in the preceding 3 months. The sample excludes loans to firms that are directly affected by the major wildfire. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-wildfire disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
$Indirect\ wildfire \times Recent\ wildfire$	9.058*	9.080**	7.816*	7.856*
	(4.405)	(4.378)	(4.487)	(4.459)
$Indirect\ wildfire$	-4.043	-4.129	-2.066	-2.119
	(2.607)	(2.530)	(2.494)	(2.447)
$Recent\ wildfire$	-5.569	-5.413	-3.870	-3.785
	(4.223)	(4.259)	(4.170)	(4.200)
N	19023	19023	19023	19023
R^2	0.754	0.754	0.769	0.769
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table A.9: Winter weather and rates

This table reports regressions of loan spread (in basis points) on borrowers' indirect winter weather exposure indicator with the occurrence of a major hurricane in the preceding 3 months. The sample excludes loans to firms that are directly affected by the major winter weather disaster. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to other disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect winter weather × *Recent winter weather*	5.248	4.089	2.083	1.389
	(6.319)	(6.351)	(7.736)	(7.613)
Indirect winter weather	-1.712	-2.254	-2.790	-2.624
	(3.772)	(3.418)	(3.342)	(3.471)
Recent winter weather	13.227*	11.184	10.021	10.118
	(7.676)	(7.715)	(7.738)	(7.758)
N	23252	23252	23252	23252
R^2	0.689	0.724	0.735	0.736
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table A.10: Climate disasters and rates (climate aggregated)

This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster exposure indicator with the occurrence of the same type of disasters in the preceding 3 months. Climate change related disasters include hurricanes, floods, and wildfires. The sample excludes loans to firms that are directly affected by these disasters. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to other disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect climate disasters × *Recent climate disasters*	10.035***	8.418***	7.409***	7.368***
	(3.086)	(2.460)	(2.403)	(2.384)
Indirect climate disasters	-9.941**	-6.778**	-6.575**	-6.530**
	(3.567)	(3.047)	(2.950)	(2.839)
Recent climate disasters	-2.299	-2.859	-3.300	-3.021
	(2.761)	(2.613)	(2.509)	(2.523)
N	18126	18126	18126	18126
R^2	0.687	0.723	0.735	0.736
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.11: Non-climate disasters and rates (non-climate aggregated)
This table reports regressions of loan spread (in basis points) on borrowers' indirect non-climate change related disaster exposure indicator with the occurrence of the same type of disasters in the preceding 3 months. Non-climate change related disasters include winter weather and earthquakes. The sample excludes loans to firms that are directly affected by these disasters. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to other disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
$Indirect\ non-climate\ disasters \times Recent\ non-climate\ disasters$	3.942	2.705	-0.023	-0.593
	(6.887)	(6.377)	(7.561)	(7.400)
$Indirect\ non-climate\ disasters$	-4.128	-4.973	-4.666	-4.613
	(3.105)	(3.120)	(3.094)	(3.208)
$Recent\ non-climate\ disasters$	9.552	7.508	7.064	7.083
	(6.859)	(5.966)	(5.870)	(5.777)
N	22114	22114	22114	22114
R^2	0.694	0.727	0.738	0.739
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.12: Robustness: seasonality and industry controls

This table reports regressions of loan spread on borrowers' indirect natural disaster indicators with the occurrence of the same type of disasters. Both climate and non-climate change related disasters are included, defined as hurricanes and earthquakes, respectively. The sample excludes loans to firms that are directly affected by those disasters. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane and non-earthquake disasters if any. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) climate change and non-climate change disasters				
	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × Recent hurricane	21.467**	21.377**	38.829**	38.982**
	(8.999)	(9.136)	(15.724)	(15.730)
Indirect earthquake × Recent earthquake		-14.736		-22.525**
		(9.280)		(9.609)
Indirect hurricane	3.390	3.883	-2.137	-2.699
	(4.167)	(4.174)	(4.023)	(3.913)
Indirect earthquake		-6.085		6.217
		(4.146)		(4.120)
Recent hurricane	0.368	0.737	-11.568	-11.690
	(3.828)	(3.856)	(10.023)	(10.021)
Recent earthquake		10.501		13.788*
		(8.126)		(7.149)
N	20463	20257	19844	19629
R^2	0.752	0.752	0.855	0.855
Bank × Year Hurricane FE	Yes	Yes	Yes	Yes
Industry × Year Quater FE	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

Table A.13: Hurricanes - excluding firms with any type of direct disaster damage
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane disaster indicator with the occurrence of the same type of disasters. We exclude loans taken out by a firm with any type of direct disaster damage in a given quarter. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	23.199**	23.873**	24.185**	23.032**
	(10.077)	(11.137)	(11.237)	(11.121)
Indirect hurricane	3.608	2.452	3.921	3.256
	(6.867)	(5.963)	(5.657)	(5.550)
Recent hurricane	1.345	-0.511	-0.661	-0.172
	(4.295)	(4.101)	(3.940)	(3.846)
N	16910	16910	16910	16910
R^2	0.713	0.742	0.751	0.753
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table A.14: Climate disasters and rates (employment weighted operations)
This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster indicator with the occurrence of major hurricanes. We calculate firms' exposure to climate hurricane prone areas using employment weights, rather than operations weights. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane (employment) × *recent hurricane*	14.298*	12.534	14.714*	12.918*
	(7.257)	(7.631)	(7.393)	(7.432)
Indirect hurricane (employment)	0.162	0.350	0.884	0.791
	(5.056)	(4.829)	(5.006)	(4.763)
N	21262	21262	21262	21262
R^2	0.696	0.730	0.713	0.742
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.15: Robustness: Main test excluding financial crisis
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a hurricane in the preceding 3 months. Loans during the great financial crisis from July 2007 to July 2009 are excluded. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties subject to disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	17.623**	19.503**	18.340**	19.917**
	(7.485)	(7.912)	(8.042)	(8.112)
Indirect hurricane	1.611	1.913	1.998	2.199
	(5.132)	(4.493)	(4.450)	(4.036)
recent hurricane	1.171	-1.787	2.407	-0.756
	(3.483)	(3.382)	(3.328)	(3.372)
N	20372	20372	20372	20372
R^2	0.697	0.731	0.714	0.743
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.16: Robustness: Rates and climate change related disasters - alternative treatment definitions

This table reports regressions of loan spread on various measures of borrowers' indirect hurricane exposure interacted with the occurrence of a major hurricane in the preceding 3 months. *Indirect hurricane (general)* is an indicator for firms in the top quintile of hurricane exposure, sorted by the entire sample (rather than at a given point of time as in our main analysis). *Indirect hurricane (general, continuous)* is the continuous version of the same quintiles. *Indirect hurricane continuous* is the continuous version of the quintiles used in our main specification (sorted within loans). *Any indirect hurricane* is an indicator for loans with any exposure to hurricanes (defined as any operations inside counties that are in the top decile of counties by hurricane damage in a rolling 10 year window). Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane general $\times$ *recent hurricane*	18.772*			
	(9.550)			
Indirect hurricane general continuous $\times$ *recent hurricane*		4.536**		
		(2.020)		
Indirect hurricane continuous $\times$ *recent hurricane*			4.751**	
			(2.066)	
Any indirect hurricane $\times$ *recent hurricane*				17.142**
				(7.152)
N	21262	21262	21262	21262
R^2	0.743	0.742	0.742	0.742
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	Yes	Yes

Table A.17: Time varying attention to climate change and rates - google trends data

This table reports regressions of loan spread on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 12 months. *Google trends index* is the raw measure of google searches for the term climate change during 2004 to 2019, scaled to 100 for the maximum value. *Above median Google trends* is an indicator for months with above median search interest. *medium (top) tercile Google trends* are indicators for months with search interest in the second (third) tercile during the sample. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and google interest			
	Spread		
	(1)	(2)	(3)
Indirect hurricane × *recent hurricane*	-21.277	4.436	16.213
	(26.132)	(12.620)	(13.994)
Indirect hurricane × *recent hurricane* × *Google trends index*	2.331		
	(1.320)		
Indirect hurricane × *recent hurricane* × *above median Google trends*		61.634**	
		(22.167)	
Indirect hurricane × *recent hurricane* × *medium tercile Google trends*			21.959
			(47.056)
Indirect hurricane × *recent hurricane* × *top tercile Google trends*			46.067**
			(18.472)
N	9472	9316	9472
R^2	0.777	0.777	0.777
Bank× Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table A.18: Time varying attention to climate change and rates - Reuters news data

This table reports regressions of loan spread on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 12 months. *News attention index* is the raw measure of articles indexed by Reuters mentioning a connection between storms and climate change as a fraction of all articles mentioning storms during 2004 to 2019, standardized. *Above median news attention index* is an indicator for months with above median index. *medium (top) tercile news attention index* are indicators for months with search interest in the second (third) tercile during the sample. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and google interest			
	Spread		
	(1)	(2)	(3)
Indirect hurricane × *recent hurricane*	17.329	8.662	-1.541
	(10.174)	(13.987)	(19.240)
Indirect hurricane × *recent hurricane* × *news attention index*	19.025*		
	(10.495)		
Indirect hurricane × *recent hurricane* × *above median news attention index*		22.604	
		(20.516)	
Indirect hurricane × *recent hurricane* × *medium tercile news attention index*			-1.876
			(39.305)
Indirect hurricane × *recent hurricane* × *top tercile news attention index*			47.311*
			(25.392)
N	14979	14979	14979
R^2	0.770	0.770	0.770
Bank× Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table A.19: Time varying attention to climate change and rates - IPCC reports

This table reports regressions of loan spread on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 12 months. *IPCC* is a time indicator for periods within 24 months after the release of the third (in 2001), the fourth (in 2007), and the fifth (in 2013) IPCC reports. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and IPCC reports				
	Spread			
	(1)	(2)	(3)	(4)
$Indirect\ hurricane \times recent\ hurricane$	11.846	11.029	11.727	11.230
	(9.212)	(9.420)	(9.590)	(9.723)
$Indirect\ hurricane \times recent\ hurricane \times IPCC$	94.216***	95.875***	88.214***	87.018***
	(30.131)	(30.426)	(26.075)	(26.672)
N	20071	20071	20071	20071
R^2	0.704	0.738	0.749	0.750
Bank$\times Year\ FE$	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes