The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters and Loan Pricing

Finance Working Paper N° 889/2023
March 2023

Ricardo Correa
Federal Reserve Board

Ai He
University of South Carolina

Christoph Herpfer
Emory University

Ugur Lel
University of Georgia and ECGI

ECGI Working Paper Series in Finance

The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters and Loan Pricing

Working Paper N° 889/2023
March 2023

Ricardo Correa
Ai He
Christoph Herpfer
Ugur Lel

We thank Brigitte Roth Tran and Mathias Kruttli for helpful suggestions and for sharing the code to map NETS to Compustat. We would also like to thank David Aikman, Matias Ossandon Busch, Mark Carey, Alain Chaboud, Yongqiang Chu, John Cochrane, Nuri Esahin, Erik Gilje, Matthew Gustafson, Kristine Hankins, Victoria Ivashina, Don Morgan, Ryan Lewis, Lilian Ng, Steven Ongena, Toan Phan, Kunal Sachdeva, Christoph Schiller, Mike Schwert, Roger White, Constantine Yannelis, Yun Zhu, and seminar and conference participants at the NBER Summer Institute, the RCFS Winter Conference, the European Finance Association annual meeting, SFS Cavalcade, the Northern Finance Association annual meeting, the Wharton Conference on Climate and Commodities, the John Hopkins Carey Finance Conference, the Pre-WFA Early Career Women in Finance Conference, Qatar Center for Global Banking and Finance, the FDIC/JFSR Bank Research Conference, the IBEFA Summer Meeting, European Commission Summer School on Sustainable Finance, De Nederlandsche Bank (DNB), UCLA Climate Adaptation Research Symposium, FMA Global Conference in the Middle East, the BOCA Corporate Finance conference, the Midwest Finance Association annual meeting, Paris December Finance Meeting, the Eastern Finance Association meeting, the CEMLA-Dallas Fed financial stability workshop, University of South Carolina (Darla Moore), Emory University (Goizueta), Federal Reserve Board, University of North Carolina at Charlotte (Belk), University of Virginia (Darden), and Southwestern University of Finance and Economics (China). The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System. All remaining errors are our own.

Abstract

Banks price physical climate change-related risks after observing natural disasters linked to climate change. We isolate this updating process by identifying loans to borrowers at risk of, but not-directly affected by, climate change-related disasters. Loan spreads for these borrowers spike in both primary and secondary markets following such disasters and banks adjust internal probabilities of default, consistent with higher perceived credit risk. However, we also find evidence of overreaction due to salience, as the change in spreads is short-lived and amplified by media attention. This salience is associated solely with climate change-related disasters and impacts investment decisions at bank-dependent firms.

Keywords: Banks, climate change, loan pricing, natural disasters

JEL Classifications: G21, Q51, Q54

Ricardo Correa
Senior Adviser
Federal Reserve Board
20th and C ST N.W
Washington, DC 20551, USA
e-mail: ricardo.correa@frb.gov

Ai He
Assistant Professor
University of South Carolina
1014 Greene St
Columbia, South Carolina 29208, USA
e-mail: ai.he@moore.sc.edu

Christoph Herpfer*
Assistant Professor of Finance
Emory University
1300 Clifton Road
30322 Atlanta, Georgia, USA
e-mail: christoph.herpfer@emory.edu

Ugur Lel
Nalley Distinguished Chair In Finance, Associate Professor
University of Georgia, Terry College of Business
Amos Hall 620 South Lumpkin Street
Athens, GA 30602 , USA
e-mail: ulel@uga.edu

*Corresponding Author

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

Ricardo Correa† Ai He‡ Christoph Herpfer§ Ugur Lel¶

March 3, 2023

Abstract

Banks price physical climate change-related risks after observing natural disasters linked to climate change. We isolate this updating process by identifying loans to borrowers at risk of, but not-directly affected by, climate change-related disasters. Loan spreads for these borrowers spike in both primary and secondary markets following such disasters and banks adjust internal probabilities of default, consistent with higher perceived credit risk. However, we also find evidence of overreaction due to salience, as the change in spreads is short-lived and amplified by media attention. This salience is associated solely with climate change-related disasters and impacts investment decisions at bank-dependent firms.

JEL Classifications: G21, Q51, Q54

Keywords: Banks, climate change, loan pricing, natural disasters

*We thank Brigitte Roth Tran and Mathias Kruttli for helpful suggestions and for sharing the code to map NETS to Compustat. We would also like to thank David Aikman, Matias Ossandon Busch, Mark Carey, Alain Chaboud, Yongqiang Chu, John Cochrane, Nuri Esahin, Erik Gilje, Matthew Gustafson, Kristine Hankins, Victoria Ivashina, Don Morgan, Ryan Lewis, Lilian Ng, Steven Ongena, Toan Phan, Kunal Sachdeva, Christoph Schiller, Mike Schwert, Roger White, Constantine Yannelis, Yun Zhu, and seminar and conference participants at the NBER Summer Institute, the RCFS Winter Conference, the European Finance Association annual meeting, SFS Cavalcade, the Northern Finance Association annual meeting, the Wharton Conference on Climate and Commodities, the John Hopkins Carey Finance Conference, the Pre-WFA Early Career Women in Finance Conference, Qatar Center for Global Banking and Finance, the FDIC/JFSR Bank Research Conference, the IBEFA Summer Meeting, European Commission Summer School on Sustainable Finance, De Nederlandsche Bank (DNB), UCLA Climate Adaptation Research Symposium, FMA Global Conference in the Middle East, the BOCA Corporate Finance conference, the Midwest Finance Association annual meeting, Paris December Finance Meeting, the Eastern Finance Association meeting, the CEMLA-Dallas Fed financial stability workshop, University of South Carolina (Darla Moore), Emory University (Goizueta), Federal Reserve Board, University of North Carolina at Charlotte (Belk), University of Virginia (Darden), and Southwestern University of Finance and Economics (China). The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System. All remaining errors are our own.

†Federal Reserve Board, Division of International Finance, 20th and C ST N.W., Washington, DC 20551; ricardo.correa@frb.gov.

‡University of South Carolina, Darla Moore School of Business, 1014 Greene St, Columbia, South Carolina 29208, ai.he@moore.sc.edu.

§Corresponding author. Emory University, Goizueta Business School, 1300 Clifton Road, 30322 Atlanta, Georgia; christoph.herpfer@emory.edu.

¶University of Georgia, Terry College of Business, B363 Amos Hall 620, South Lumpkin Street, Athens, GA 30602;ulel@uga.edu.

1 Introduction

We investigate whether physical climate change risks are priced in the corporate loan market. The potential for increased frequency and severity of extreme weather events due to climate change can have devastating effects on the economy, including damage to physical assets and disruptions to operations and supply chains (Stern, 2007). With regulators increasingly worried about the potential financial risks associated with climate change, it is crucial to understand whether market participants are aware of and price climate change-related physical risk.[1] However, the majority of physical risk is expected to manifest towards the end of the century (Hong, Karolyi, and Scheinkman, 2020). The long delay before these effects fully unfold means it is unclear if shorter-lived assets, such as loans, should reflect them, as the relevance of these risks from today's perspective depends heavily on discount rates (Nordhaus, 2010; Weitzman, 2009). 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, with an emphasis on estimating discount rates to capture future long-run damages.[2] In contrast, we investigate a novel channel by which climate change plausibly shapes economic risks today – physical risk caused by the potential escalation of certain extreme weather events.

According to climate scientists, hurricanes, wildfires, and floods are already intensifying in severity or in frequency in North America because of climate change.[3] These disasters are likely the first channel through

[1] Numerous regulators and central banks, including the Bank of England (Bank of England, 2022) and the European Central Bank (European Central Bank and European Systemic Risk Board, 2022), have issued warnings about climate change in recent years. As a prominent example, the Financial Stability Board, an international standard setting body, has described in recent publications (Financial Stability Board, 2020) how climate change can have destabilizing effects on the financial system.

[2] See, for example, Giglio, Maggiori, and Stroebel (2015); Giglio, Maggiori, Rao, Stroebel, and Weber (2021); Bernstein, Gustafson, and Lewis (2019); Murfin and Spiegel (2020a); Baldauf, Garlappi, and Yannelis (2020); Murfin and Spiegel (2020b). One notable exception is Ivanov, Kruttli, and Watugala (2020), who focus on contemporaneous effects of climate change on bank lending through regulatory responses rather than physical damages.

[3] The United Nations Intergovernmental Panel on Climate Change (IPCC) (Masson-Delmotte, Zhai, Pirani, Connors, Péan, Berger, Caud, Chen, Goldfarb, Gomis, Huang, Leitzell, Lonnoy, Matthews, Maycock, Waterfield, Yelekçi, Yu, and Zhou, 2021) provides extensive discussions of these phenomena. Recent studies attribute the increased severity of several natural disasters to climate change. The balance of evidence suggests that hurricanes have become more severe in recent years due to climate change, and their landfalls have caused increasing damage in North America (Knutson, Camargo, Chan, Emanuel, Ho, Kossin, Mohapatra, Satoh, Sugi, Walsh, and Wu, 2019; Nordhaus, 2010; Risser and Wehner, 2017; Van Oldenborgh, Van Der Wiel, Sebastian, Singh, Arrighi, Otto, Haustein, Li, Vecchi, and Cullen, 2017) and worldwide (Kossin, Knapp, Olander, and Velden, 2020). Similar patterns are reported for a range of other types of severe climate change-related weather events (Stern, 2007; Mendelsohn and Saher, 2011), for example, floods (Van Der Wiel, Kapnick, Van Oldenborgh, Whan, Philip, Vecchi, Singh, Arrighi, and Cullen, 2017) and wildfires (Abatzoglou and Williams, 2016; Gillett, Weaver, Zwiers, and Flannigan, 2004; Williams, Abatzoglou, Gershunov, Guzman-Morales, Bishop, Balch, and Lettenmaier, 2019). The impact of these severe weather episodes can potentially become significant, as Stern (2007) estimates that by the mid-21st century, extreme weather events alone could cost 0.5% to 1% of global GDP annually.

which physical risks associated with climate change directly affect borrowers; therefore, they comprise a perfect laboratory to overcome the long-term horizon challenge of climate change (Giglio et al., 2021).[4] Our paper links physical climate change risk with lenders' perception of credit risk and loan terms, as well as borrowers' reactions to these changed lending terms.

One way to assess the effect of climate change-related natural disasters on firms' borrowing costs is to analyze the loan spreads charged by banks after disasters directly hit borrowers. While this approach yields evidence on financial institutions' pricing of disaster risk, it cannot distinguish between the direct effect of the disaster on loan spreads, such as physical damage or disruptions of business operations, and the updated expectations of lenders regarding the future frequency and severity of such disasters (Nordhaus, 2010). Instead, our identification strategy relies on observing changes in loan spreads for borrowers with operations located in disaster-prone areas, but not directly affected by a specific event. We refer to them as *indirectly affected* or *at-risk, but unaffected* borrowers. This approach enables us to separate the immediate impact of disaster strikes from the updated expectations of lenders concerning the future effects of climate change-related events.

To determine companies' exposure to various types of physical climate risk, we utilize 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 time-varying measures of their exposure to various types of disasters resulting from the geographic footprint of their operations. This operation-weighted disaster exposure allows us to measure borrowers' general vulnerability to certain types of disasters.

Using these exposure measures and loan spreads at origination from the syndicated loan market, we find that, following a hurricane landfall, banks charge about 19 basis points higher spreads on loans to *indirectly affected* borrowers. This increase in loan spreads is economically sizable, as it represents about 10% of the unconditional spread charged on loans included in the sample and is comparable to the impact on spreads of a one notch rating

[4] Importantly, these types of climate risks are already being priced by equity 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 portfolios today or within two years.

downgrade.[5] We also use pricing information from the secondary loan market and find that physical climate risks are captured in the prices quoted in that market. We observe a 2.1% decline in loan prices following recent climate change-related natural disasters. The implied increase in yield from this price move is about two times larger in economic magnitude than that documented in the primary market and provides evidence that climate change affects loan pricing beyond origination. This is important, as it suggests that a firm's selection decision whether to raise funds in the primary market does not drive our result. Moreover, this result suggests that non-bank investors in the secondary market, such as loan funds and collateralized loan obligation (CLO) managers, also price the climate risk embedded in these types of loans.

Next, we proceed to explore the mechanisms through which climate risks may be incorporated into loan spreads. As noted previously, the potential change in the observed intensity of climate-related natural disasters could elevate the perceived credit risk of at-risk borrowers. Consistent with this conjecture, we find that credit risk plays a role in driving up the spreads in two sets of tests. First, using banks' internal model-based assessments of corporate borrowers' probabilities of default (PDs), we observe a significant increase in the PDs of indirectly affected borrowers after a hurricane by about one percentage point, or one-fifth of a standard deviation. However, the change in PDs can only explain about one-fifth of the observed change in loan spreads of at-risk firms, or four basis points. Second, we observe that the effect of indirect disaster strikes is amplified for the most bank-dependent firms and those with the highest ex-ante default risk.

We then investigate whether the portion of the increase in spreads not explained by credit risk reflects overreaction driven by salience associated with extreme events (Kahneman and Tversky, 1979). As a first test, we analyze the dynamics of the reaction of spreads to climate-related severe weather events. We find that, across the primary and secondary loan markets, yields revert back down within one quarter following an indirect hurricane hit. The transient nature of these effects is consistent with overreaction to salient, extreme events.

In further tests, we examine whether the loan-spread increase for at-risk firms varies with attention to climate change. We measure time-varying climate change attention using the Wall Street Journal climate change news

[5]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 climate change-related natural disasters, are widely observed and relatively frequent. We show in the Internet Appendix that our results are quantitatively and qualitatively very similar for other disasters associated with climate change, namely wildfires and floods. A one notch downgrade is associated with a roughly 20 basis point increase in spreads for investment grade rated debt.

index (Engle, Giglio, Kelly, Lee, and Stroebel, 2021), Google trends data, and a proprietary index extracted from Reuters news articles. Our results consistently show that the increase in spreads for at-risk borrowers is strongest at times of high attention to climate change. Similarly, we find cross-sectional evidence that banks which pay closer attention to climate change-related issues, measured using transcripts of earnings conference calls (Sautner, van Lent, Vilkov, and Zhang, 2022a), react more strongly. The link between attention to climate change and the loan price reaction to disasters in both the time series and cross section provides further evidence that banks may overreact to climate information and that the salience of climate change events may impact those decisions.

We then investigate two dimensions in which the salience to climate change-related disasters exhibited by banks in our setting is different from the salience observed in non-financial firms following extreme events (Dessaint and Matray, 2017). First, we show that the overreaction in loan prices is topical, that is, unique to climate change. We find no evidence that loan spreads increase for firms indirectly affected by disasters unrelated to climate change (e.g., earthquakes and winter weather). This stands in contrast to the literature on salience of extreme events, where non-financial firm executives exhibit salience *even* with respect to uninformative earthquakes (Dessaint and Matray, 2017).[6] If our results merely reflect banks' salience to rare disasters, rather than a more topical salience associated with climate change, we should see the same spike in spreads for indirectly affected firms following earthquakes or winter weather, which is not what we find. In contrast, when we repeat our tests with other disasters which are getting worse with climate change (floods and wildfires), we find similar results as for hurricanes. To the best of our knowledge, this is the first paper to document topical climate-change specific salience.

A second novel finding in our paper is that we document salience for a new group of agents. Corporate executives located close to areas affected by natural disasters are shown to make financial decisions that are driven by salience (Dessaint and Matray, 2017), yet loan spreads are not set by corporate executives. Instead, they are set by commercial bankers in locations usually different from those of executives borrowing in the syndicated loan market (Herpfer, 2021). While we find a weak link between bankers' pricing decisions and their personal exposure to hurricanes based on their locations, our main results remain robust. This finding implies that salience on the

[6] In classifying disasters as climate change related, we follow the IPCC's long-standing assessments, which find no evidence of increased severe winter weather in North America due to climate change. These assessments instead show that warmer winters are linked to climate change.

personal level of bankers cannot explain our findings, and that the overreaction we observe is driven by salience at the organizational level. The results in our study point towards a nuanced, different type of salience, in which banks try to learn from disasters about climate risk of at risk, but unaffected firms, yet overshoot.

Finally, we examine whether the climate change-related salience of lenders spills over into the investment decisions of borrowers. We find that the most bank-dependent, indirectly hit firms, which experience higher spreads and lower loan amounts, 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. These findings imply that changes in banks' lending terms due to climate change-related risk may be affecting firms through their cost of funding.

To assess the robustness of our findings, we investigate whether various types of spillovers are responsible for our results. We find that results hold in various exercises controlling for spillovers through banking networks (e.g. Cortés and Strahan, 2017; He, 2019), the borrowers' internal capital network, customer-supplier links (Barrot and Sauvagnat, 2016), or regional spillovers through geographic proximity. Results are similarly not driven by a host of other factors, including the seasonality of hurricanes 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 other types of natural disasters. The staggered aspect of natural disasters also mitigates the concern about potentially omitted concurrent events. Our results are further robust to various measures of attention, alternative measures of firms' geographic footprints, alternative measures of hurricane exposure, placebo exercises regarding the timing of hurricanes, and a wide range of model specifications.

Our paper contributes to the nascent literature on how investors respond to climate change, as we provide estimates on how loan market participants adjust credit spreads for borrowers exposed to physical climate change risk. 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 physical climate change risk to corporate loan costs.[7] The extant evidence for corporations is largely limited to long-lived assets such as equity securities. Notably, Engle et al. (2021) develop a new measure of climate change risk hedging

[7]A parallel literature analyzes the effect of natural disasters on bank lending. Schüwer, Lambert, and Noth (2019) assess the relation between natural disasters and banks' capital structure, while Koetter, Noth, and Rehbein (2020) and Cortés and Strahan (2017) explore banks' reallocation of funds from unaffected to affected areas after natural disasters. Even though our paper emphasizes corporate loan pricing instead of the volume of lending, we carefully control for the dynamics observed in those related studies.

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. There is evidence that the salient overreaction to disasters by executives affects firms' lending terms (Huang, Jiang, Xuan, and Yuan, 2022) and is also present for fund managers (Alok, Kumar, and Wermers, 2020). On the bank lending side, Delis, De Greiff, 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 (2022) and Ivanov et al. (2020) find that firms with higher climate regulatory risk face higher bond and loan yields, and Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2019) and Painter (2020) show an effect of future projected sea level rises on long term municipal bond yields.

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 prompted 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 the increase in loan spreads is transitory and driven largely by salience to climate risks may have consequences from a regulatory perspective. For example, if banks abruptly adjust their risk assessments associated with these types of disasters, they could increase firms' funding costs materially. Our results on corporate reactions imply a risk that the most affected firms internalize the threat of adverse funding shocks by adjusting their financing and investment activity.

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, as is the case in Florida for hurricanes and California for wildfires (Nordhaus, 2010). In our analytical framework, we overcome this challenge by differentiating between two facets of the impact of disasters on loan spreads: (a) the direct effects 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* of these disasters, but *not directly affected* at a given point in time. These borrowers are identified based on their operation in at-risk areas from the detailed historical disaster hit records. 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.

We then proceed to test the mechanism through which banks incorporate information from climate related disasters into their pricing decisions. If banks assess a higher probability of defaults associated with climate change-related natural disasters, they will update their credit risk models to reflect this information. In addition, if banks fear increased credit risk as a result of climate change-related disasters, they will respond particularly strongly for the most at-risk borrowers.

Hypothesis 2: The pricing of climate change-related disasters is driven by a perceived increase in credit risk.

A potential confounding issue with this setup is that any change in the loan pricing observed for at-risk firms may simply capture a reaction of banks to any type of rare disaster or tail risk, 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 3: For disasters that are not amplified by climate change, there should be no effect on loan spreads for indirectly affected borrowers.

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 natural disasters, with a distinction on their relation to climate change, which we describe in the next section.

3 Data and sample

To assess the exposures of firms to physical risks, we need to construct a dataset composed of three different layers. The first layer captures the historic exposure of each county to various natural disasters. The second layer captures the geographic footprint of firms, that is, each firm's operations per county. 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 from 1960 to the present. The 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 capture 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, it includes 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). These reports find substantial evidence of a link between climate change and hurricanes, wildfires, and floods, all of which we classify as climate change-related disasters. Our baseline specification focuses on hurricanes because they are widely observed, severe, and relatively frequent. To support this approach, we provide a wide range of evidence from both climate science and the perception of market participants on the link between specific disaster types and climate change in the Internet Appendix section IA.2. We use the SHELDUS data to assess the exposures of each county to these types of natural disasters and also to capture the realization of these disasters and their impact on specific geographic areas. In the Internet Appendix section IA.3, we show that our results hold for climate-related disasters beyond hurricanes.

We then contrast our findings for climate change-related disasters with those unrelated to climate change.

Among natural disasters, earthquakes are the most clearly unrelated to climate change. However, because 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) to capture the exposure of specific locations to earthquakes.[8] The data project potential maximum expected ground motions of latitude/longitude locations across the conterminous United States, and 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 related to *winter weather* in SHELDUS. We, therefore, also conduct tests of winter weather as non-climate change-related disasters.

Figure 1 and Figure 2 provide graphic representations of the exposure of each county to hurricanes and earthquakes, respectively. The maps present snapshots of our time series for 2008, in the middle of our sample period, and they show that our data on disasters reflect the expected geographic distribution, with hurricanes causing damages in the southeast and the Atlantic coast, while seismic ground motions are most active along the west coast.

[Figure 1 here]

[Figure 2 here]

We undertake two steps to select our final county-month data on natural disasters. First, we focus on disasters with aggregate damages that exceed $100 million in 2019 constant dollars to make sure we capture significant disasters. Second, for each type of disaster, we measure disaster damage in a 10-year rolling window each month and classify counties as *disaster-prone* counties for the corresponding disaster type if they are in the top 10% of counties with respect to local disaster damages. The benefit of this procedure is that it results in a simple, easily interpretable binary distinction of counties at risk of disasters, and those not at risk. Importantly, our results are economically and statistically robust to dropping each of these restrictions.

[8]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.

3.2 Data on firm and bank exposures to natural disasters

After we measure each county's exposure to natural disasters, we construct granular corporate geographic footprints to quantify each borrower's exposure to climate change-related disasters. Deutsche Bank, in a 2018 white paper, captures the intuition of our approach: "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."[9] In effect, our measure captures each firm's physical exposure to climate change through specific natural disasters, as opposed to more global exposure measures such as the ones constructed from earnings calls (Sautner et al., 2022a; Sautner, Van Lent, Vilkov, and Zhang, 2022b).

We construct detailed geographic footprints of corporations using annual snapshots of establishments from the NETS dataset from Walls and Associates.[10] We use information at the county–year–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 calculate each firm's fraction of establishments in disaster-prone counties and thus arrive at operations-weighted measures of a firm's exposure to each disaster type. We then classify a firm as *indirectly exposed* to each disaster type if its operations-weighted exposure is in the top quintile of firms.[11] For example, firms indirectly exposed to hurricanes are identified with the indicator *Indirect hurricane*. We also estimate our main specification with different definitions of the indirect hurricane exposure, including variations in the cutoff for exposure or continuous exposure definitions. Our results remain economically and statistically unchanged. More details can be found in section 7. For the earthquake exposure, because earthquakes are rather infrequent in the U.S., we calculate each firm's exposure both in this way using historic exposure, as well as through the analogous location-weighted ground motion assessment provided by USGS.

[9] A detailed overview of this and similar statements by other lenders is presented in Internet Appendix section IA.1.

[10] The NETS database contains descriptive information about each establishment starting with its location and parent company, as well as quantitative data such as employment and sales. 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 four years, the correlation of hurricane exposure is 0.94. All our results remain economically and statistically unchanged if we stop the sample in 2014.

[11] About one fifth of firm-year observations exhibit any hurricane exposure, making this definition identical to "any exposure" in the case of hurricanes. Since more firms are at small risks of other disasters, the 20% cutoff makes the fraction of treated firms comparable across the different disaster types. Our results are robust to variations in this definition.

3.3 Data on banks loans and risk assessment

In the last step of constructing 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. In total, our sample includes 21,262 loans, issued to 2,522 firms over the years from 1996 to 2019, and is restricted 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 being polluted by any potential direct effect of natural disasters, we exclude all loans of those borrowers that have suffered a direct hit from either hurricanes or earthquakes within three months of the loan origination.[12] We also obtain secondary market loan prices from Refinitiv's Loan Pricing Corporation from 2000 to 2017. The secondary market data consist of self-reported information from brokers who quote daily prices on loans.

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 2011-end and 2018 and above $100 billion thereafter are required to report this information. The PDs calculated by so-called "advanced approaches" banks are based on banks' internal risk models as proposed in the Basel II Accord. For banks that are not subject to the advanced approaches regulation, the reported PDs are based on banks' internal risk ratings. These PDs are one-year "through-the-cycle" default rates, and reflect largely model based risk assessments with relatively little human impact. 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.[13]

[12]Our results are robust to both including these firms and dropping firms with direct exposure to any type of disaster. Our results are further robust to various tests that control for spillovers of direct hits, such as removing firms with operations in counties adjacent to directly hit counties.

[13]We exclude the oil sector 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.

3.4 Sample statistics

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

[Table 1 here]

Panel A covers the 21,262 loans in our main sample. The median loan is a $649.73 million (in 2019 U.S. dollars) 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 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 large scale. Though their severity varies by type, all the disasters in our sample are considered severe because they were all declared major disasters in response to the Governors of the affected states asking for aid. 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 daily quote price of loans in the secondary market and the PDs reported by banks in their FR Y-14Q filings. The average daily quote is 95.83 with a standard deviation of 57.53. The sample mean for the PDs is 1.2% with a standard deviation of 5%. The period encompassed by the bank internal data is characterized by an economic expansion, which explains the relatively low values for PDs.

4 Climate change and loan pricing

This section presents evidence of a link between climate change and loan pricing both at loan origination and in the secondary loan market.

4.1 Empirical setup

As described in section 2, our main objective is to test for the pricing of physical climate risk in loan spreads using borrowers' exposures to natural disasters as part of the identification strategy. One 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 3 presents this analysis.

[Figure 3 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 with loan spread as the dependent variable. As shown in the figure, the effect of *direct* exposure to climate change-related disaster exhibits a small and positive time trend. Compared to the time period between 1996 and 2000, 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.[14] 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. 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 (Nordhaus, 2010). 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).

To disentangle these two separate effects of natural disasters on loan pricing, our setup does not draw inferences from firms *directly* 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, something we refer to as *indirectly hit*.

Intuitively, we hypothesize that banks update their assessments of climate change-related disasters partly by observing the effect of these events on loan performance. Consider a hypothetical case in which a bank lends

[14] Consistent with the increase in spread, we find that direct hurricane hits cause increasingly larger damages to firms' financial performance.

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. 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. The channel we attempt to isolate is a perceived increase in borrower risk as a result of climate change. Recent literature has found mixed results with respect to the effect of disasters on the overall performance of banks (Blickle, Hamerling, and Morgan, 2021; Berger, Curti, Lazaryan, Mihov, and Roman, 2022). Importantly, our setup does not require that banks overall suffer after disasters – it merely requires banks to perceive an increased credit risk for borrowers.

Formally, we use the following econometric setup to test *Hypothesis 1*:

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

All variables are explained in Appendix A.1. The outcome variable of interest is the loan spread charged to borrower i by bank m in month t. We drop all loans taken out by borrowers whose operations are directly hit by a hurricane within three months prior to loan origination; that is to say, the test is only conducted among firms that are not directly hit by a recent hurricane to avoid contamination of our results. 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 indicator of firms with operations in hurricane-prone counties and an indicator of a climate change-related disaster has occurred within three months prior to loan origination. We expect β_1 to be positive if banks update their prior expectations about the severity of climate change-related disasters after observing the recent occurrence.

In estimating equation (1), we control for a number of other factors that may influence loan spreads. 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 captures that type of risk-taking. Similarly, the indicator $Recent\ hurricane_t$ takes the value of one if a hurricane has occurred in the three months preceding the loan. This variable is not absorbed by 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 in our sample impact many borrowers, therefore we also include borrower's direct exposure to non-hurricane disasters into the time-varying firm control vector $X_{i,m,t}$, which also includes a wide range of time-varying firm controls (size, profitability, debt-to-asset ratio) and loan controls (loan type, maturity, covenants). Additionally, to ensure our estimation is not simply attributable to the spillover effect of the hurricane on a local economy that spans counties through geographic proximity, customer-supplier links, or common bank networks, we conduct a wide range of robustness checks in section 7.

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 control for a number of alternative, time invariant, explanations, such as the firm's headquarter location and 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. 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 change-related disaster. Our results remain economically and statistically significant when we include additional quarter fixed effects in section 7 to account for seasonality in the syndicated loan market (Murfin and Petersen, 2016), and results remain robust when focusing on loans issued during times where no hurricanes are threatening to hit in the near future. We cluster the standard errors ϵ by firm, to capture serial correlation of errors within the same borrower over time, and by year, to capture the arbitrary correlation of errors for loans taken out at the same point of time.

4.2 Climate change-related risks and loan pricing in the primary market

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

[Table 2 here]

The key coefficient in this specification is β_1, which captures banks' pricing of climate risks through their assessment of the impact of climate-related natural disasters on 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 rate spreads by about 17 basis points to exposed but only indirectly affected borrowers.

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 increases to 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, similar to a one notch credit rating downgrade for investment grade debt.

The evidence on the link between climate-related risks and loan pricing is consistent with lenders' stated 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 of them mention that climate change potentially intensifies these disasters and poses a material risk to the creditworthiness of borrowers. This anecdotal evidence suggests that lenders, credit rating agencies, and governments have become increasingly aware of the threat of climate change-related disasters for loans.[15] Some of the banks mention specific disasters that pose a threat to their loan portfolio. While hurricanes and storms are the most frequently mentioned

[15] As presented in Internet Appendix Table IA.1, some of these banks had already started to note natural disasters as an important risk in 2010. In 2019, all banks in this sample flag those disasters as material issues and link 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." Internet Appendix section IA.1 provides a wide range of examples for this type of awareness on the link between climate change, disasters, and credit risk.

threat, banks also mention two other disasters that, according to the IPCC, are linked to climate change: wildfires and floods. Indeed, when we repeat the tests from Table 2 defining all our measures using wildfires and floods in Internet Appendix Table IA.2 and IA.3, respectively, we find a consistent result of increased spreads for indirectly hit firms for both disaster types. These results reinforce the connection between climate change and spreads we find for hurricanes. In the final test, we examine if the results on loan spreads extend to other loan terms. Internet Appendix Table IA.4 shows that banks (marginally) lower loan amounts and shorten maturities after indirect hurricane hits. Just like higher spreads, these results are consistent with a perception of elevated credit risk on the part of banks following indirect hits from climate change-related disasters. Taken together, the results in Table 2 are consistent with *Hypothesis 1*, that banks react to hurricanes by increasing the interest rate spread charged to borrowers with significant exposure to these disasters.

4.3 Climate change-related risks and loan pricing 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. Loans in the primary market reflect both the firm's 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 weak, indirectly affected borrowers are shut out of credit markets, and they are unable to raise capital at any price for some time. 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.

To investigate whether selection in the primary loan markets affects our results, we turn to the pricing of loans in the *secondary* market. Syndicated term loans are typically transferred to other types of non-bank investors, such as loan funds and CLO managers, after origination (Lee, Li, Meisenzahl, and Sicilian, 2019). Loans quoted in this market are previously issued loans, and therefore they are not subject to the aforementioned selection concerns. The secondary market data from Refinitiv's Loan Pricing Corporation consist of self-reported information from brokers who quote daily prices on loans from 2000 to 2017. In an event study setting, we include daily quotes of 1319 existing loans 12 weeks before or after a hurricane hit, while excluding loans from firms directly affected by the hurricane. We then test the quote price reaction of these loans for firms that suffer an indirect hurricane hit.

We report results from this test in Table 3, in which the outcome variable is the logarithm of each loan's daily average quote price. Column 1 includes no additional control variables, and column 2 adds 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.

[Table 3 here]

The results in Table 3 confirm our findings from the study of loan spreads at origination. Across all columns, we observe a decline in the secondary market loan prices of at-risk borrowers by between two and three percentage points after a hurricane. Thus, investors in the secondary market price physical climate change risk as a result of increasingly severe hurricanes.

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, therefore, 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. Jointly, these findings from the secondary loan market data not only alleviate concerns that selection drives our initial findings, but also show that a group of different investors, such as CLOs and loan funds, changes their behavior similarly to banks issuing loans in the primary market.

5 Credit risk and exposure to climate change-related risks

The next set of tests investigates the fundamental drivers of the increase in spreads for at-risk firms around climate change-related natural disasters, as stated in *Hypothesis 2* of section 2. This section focuses on assessing whether the pricing of climate-related risks in loan spreads described in the previous section is driven by banks' assessment of the creditworthiness of at-risk firms.

5.1 Climate change risk and banks' assessment of default probabilities

In our first set of tests, we analyze banks' assessments of the creditworthiness of corporate borrowers by using PDs sourced from the U.S. "credit register." The objective of this exercise is to determine whether the output from banks' credit risk models is consistent with the higher spreads charged to at-risk borrowers shown in the previous section, which would support the notion that banks are adjusting their models to reflect the potential impact of climate change on the frequency and intensity of some natural disasters. PDs are reported by large U.S. banks as part of their stress test-related regulatory filings. This measure should capture the banks' "through-the-cycle" expectations of a borrower's likelihood of default.[16] 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 of at-risk firms experience persistent increases after the advent of climate change-related natural disasters.

In Table 4, we present a specification similar to the one used to analyze the secondary loan pricing data, but using banks' internally generated PDs as the dependent variable. In this specification, we can track the same bank-borrower pairs over time, mitigating concerns related to selection. However, different from the tests using syndicated loan originations, the sample period is much shorter (end-2014 to end-2019) due to data availability, which limits the power of our tests.[17]

[Table 4 here]

[16]These PDs are part of the regulatory framework set under Basel II and are typically estimated using internal models managed by large banks, specifically those following the advanced approach (Christensen, 2007).

[17]As in our main specification, we define a county as at risk of hurricanes if it has suffered any hurricane damage in a ten year rolling window. Due to this data covering a different time period than our main sample, this procedure slightly expands the number of counties considered at-risk.

In the first two columns, we examine the contemporaneous effects and find that banks increase the PDs of at-risk borrowers between 0.8 and 1.1 percentage points after a hurricane occurrence. This 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. This column shows that these effects are persistent and jointly statistically significant, as shown by the sum of coefficients 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 suggest that banks are taking into account some of the natural disaster risks associated with climate change in their risk management, especially in recent years, as some large hurricanes have directly impacted firms in some areas leading to an increase in the likelihood of loan delinquencies.[18] However, changes in the PDs do not fully explain the changes in spreads reported in the previous sections. Setting aside differences in the composition of loans across the two datasets (both in terms of the cross-section of loans and the time series), and since we find no change in estimated losses given default in unreported tests, a simple back-of-the-envelope calculation yields that changes in PDs explain only about one-fifth of the changes in spreads.[19]

5.2 Cross sectional effects on high-credit-risk borrowers

We further check the credit risk effect of climate-related disasters by assessing the pricing of loans across firms with different levels of creditworthiness. A financially healthy borrower can weather the damage from a climate change-related disaster with no impact on its ability to repay its debt. In contrast, borrowers who are close to bankruptcy have the highest risk of defaulting on loans as a result of their exposure to this type of disaster. If banks indeed price the increased default risk from climate change disasters, the price reaction should be more pronounced among borrowers who are more at risk of bankruptcy. We empirically test this conjecture by estimating the most saturated model of Table 2, which is column 4, and three proxies for borrower risk.

[18] In unreported results, we find that the likelihood of a firm becoming delinquent on their loans after a direct hurricane hit increased significantly in the 2016 and 2017 hurricane seasons. Those years featured hurricanes that produced large losses, including Harvey, Irma, Maria, and Matthew, which may have influenced banks' credit risk models.

[19] We use the average loss given default reported in the FR Y-14Q submissions and multiply it by the roughly one percentage point increase in PDs estimated in our specifications. That implies a change in the spread of about four bps, or about one-fifth of the roughly 19 bps that we observe in the data.

[Table 5 here]

Table 5 reports results from this estimation. First, in column 1, we interact *Indirect* $hurricane_{i,t}$ × *Recent* $hurricane_t$ with *Market* $leverage_{i,t}$, firms' leverage ratios measured at the time of loan origination. We normalize market leverage such that the coefficient can be interpreted as the effect of a one standard deviation increase in leverage. For ease of exposition, we do not tabulate lower interactions and control variables of each regression. The interaction term *Indirect* $hurricane_{i,t}$ × *Recent* $hurricane_t$ × *Market* $leverage_{i,t}$ captures the differential effect of an indirect hurricane on firms with elevated credit risk. Consistent with banks reacting more strongly when borrowers are less financially stable, we find that the coefficient on the triple interaction term is 25.3, while the double interaction term *Indirect* $hurricane_{i,t}$ × *Recent* $hurricane_t$ stays around 17.5. The effect on highly leveraged borrowers is therefore more than twice as large as the effect for the overall sample.

One specific way through which natural disasters threaten firms' creditworthiness is through the threat of destroying physical assets, particularly those that can secure loans. In column 2, we estimate the coefficient for the triple interaction term *Indirect* $hurricane_{i,t}$ × *Recent* $hurricane_t$ × $Tangibility_{i,t}$, where $Tangibility_{i,t}$ captures borrowers' tangibility of assets. For ease of exposition, tangibility is normalized to a mean of zero and standard deviation of one. Consistent with the threat to physical assets amplifying the effect of hurricanes, the coefficient estimate on the triple interaction term is 14.5, which is a statistically and economically significant amplification of the base effect.

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). This column shows a coefficient estimate of 45.98 on the interaction term *Indirect Indirect* $hurricane_{i,t}$ × *Recent* $hurricane_t$ × *Non–investment* $grade_{i,t}$. 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.[20] In addition, firms without investment grade ratings have less access to alternative capital sources such as the bond market, making them particularly bank dependent and hence susceptible to banks' perceived climate change risk.

In sum, the findings in this section lead us to partially reject *Hypothesis 2*. Although there is a link between the increase in spreads and the perceived credit risk of at-risk firms, our estimates on banks' internal credit models

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

cannot account for the main portion of increased spreads. In the next section, we explore other mechanisms that may influence these spreads.

6 Pricing overreaction to climate change

The results presented in the previous section suggest that about one-fifth of the increase in syndicated loan market spreads for at-risk firms observed after hurricanes can be attributed to credit risks associated with climate change-related natural disasters. This section explores the extent to which the remaining portion of the increase in spreads is driven by an overreaction to these events, and the potential mechanisms through which this type of overreaction may take place.

6.1 Is the effect of climate change-related disasters on spreads persistent?

A key step to assess the mechanism driving the "excess" increase in spreads for at-risk firms is determining whether the change in spreads for these firms is permanent or transitory. For instance, if the effects are transitory, it is likely that our results reflect some overreaction or salience to the risks produced by climate change-related natural disasters.

Thus, we first assess the persistence of climate-related loan pricing adjustments in our main specification by estimating the evolution of loan spreads due to an indirect climate change-related disaster. We display the key coefficient in Figure 4. More specifically, this figure plots estimated coefficients on $Indirect\ hurricane_{i,t} \times Recent\ hurricane_{t+\tau}$, with τ taking -2 to 4, so that it shows the dynamics of spread reaction in the primary market from two quarters before to four quarters after a hurricane hit. We observe a positive and statistically significant coefficient estimate in the quarter of the hurricane strike, but this effect vanishes quickly.

[Figure 4 here]

In unreported results, we find that the effect in the secondary market seems to be even more transient than the effect in primary markets estimated here, while the effect on banks' internal credit risk assessments, as shown in Section 5.1, seems to be slightly more persistent. These figures overall suggest that a portion of the increase in spreads for at-risk firms is driven by an overreaction to climate change, potentially due to salience. Next, we assess the drivers of the pricing overreaction to these events.

6.2 Is the pricing overreaction influenced by attention to climate change?

Banks' updating about physical climate change risk depends on their ability to observe it, and there is extensive evidence that investor attention is limited and can be focused on major events (Klibanoff, Lamont, and Wizman, 1998). In our setting, this argument suggests that climate change-related risk is amplified in periods of high attention to climate change. We test the influence of this behavioral response by exploiting variations in the attention to climate change both in the time series and the cross-section.

First, we use the Wall Street Journal (WSJ) index introduced in Engle et al. (2021) to measure time-varying attention to climate change. This index measures the frequency in which climate change vocabulary appears in the WSJ. It captures the overall market attention to the topic and spikes during times of particular attention to climate change. Panel A in Figure 5 displays the evolution of the WSJ index, which reveals two specific patterns. First, the index has a positive trend, capturing the increasing attention to climate change over time, as featured in the news. Second, the index peaks during widely covered events, such as the 2009 UN climate conference in Copenhagen, the release of the Third National Climate Assessment in 2014, and the Paris Agreement at the end of 2015. Note that the index ends in June 2017, making the sample slightly smaller than our main estimations.

[Figure 5 here]

We supplement this figure with a regression analysis of the time-varying nature of climate change pricing in Table 6. These tests are similar to those in our main specification, except for the addition of triple interactions on standard regressors $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ and measures of climate change attention based on the WSJ index. We expect the coefficient estimate on this interaction term to be positive if banks pay more attention to climate change following periods of elevated attention to the topic.

[Table 6 here]

In column 1 of Table 6, 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 an additional measure 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 2019, and in Internet Appendix Table IA.5 we re-estimate our findings from the WSJ attention index with this alternative measure of attention. We also construct a third index based on news reports captured in Refinitiv's Machine Readable News (MRN) Reuters Daily News Feed database, and specifically measure the connection between climate change and storms described in these articles, with results in Internet Appendix Table IA.6. The evolution of these indices is presented in panels B and C of Figure 5.[21] Our findings are robust to these alternative measures.

Second, we sharpen our inference by examining cross-sectional differences in banks' awareness of climate change risk, as opposed to the purely time-varying measures reported above. Applying text-based measures created by Sautner et al. (2022a) which directly capture banks' discussion of climate change risk or exposure in earnings call meetings, we identify banks that express concerns over climate change. In columns 1 and 2 of Table 7, we find that banks elevate loan spreads substantially more if, in their earning call meetings right after a hurricane hit, they discuss climate change risk or climate change exposure.

[Table 7 here]

All told, we find that pricing effects are amplified by attention to climate change both in the time series of general media attention and in the cross-section of the awareness for specific banks. This suggests that the type of salience that bankers face is substantial and directly related to the topic of climate change.

[21] The Google search index exhibits similar properties to the WSJ index, that is, it also has a positive trend and peaks during salient climate-related events. The index based on Reuters articles is somewhat different, as it focuses on references to storms, including hurricanes, and their link to climate change. As expected, this index peaks during periods of large hurricane events and during periods when climate change-related studies are published or climate change is covered in popular media.

6.3 What are the drivers of loan pricing overreaction?

We begin by examining the potential explanation of overreaction as a function of salience in the form of a behavioral bias exhibited by individuals. If lenders update their beliefs about climate change after observing natural disasters due to salience, they should update most strongly for disasters with the most novel information because of the availability heuristic (Kahneman and Tversky, 1979). In Appendix Table IA.7, we test this conjecture by isolating hurricanes with large degrees of novel information based on three measures. We find that pricing effects are indeed amplified for hurricanes that are unusually destructive, unusually large, and those striking novel locations. These results are also consistent with models of salience driven by costly information acquisition (Afrouzi, Kwon, Landier, Ma, and Thesmar, 2020).

In a related study which focuses on firms' salience to natural disasters, Dessaint and Matray (2017) carefully isolate firms that are not objectively at risk of hurricanes, but whose executives are geographically exposed to a nearby hurricane. These managers increase their firms' cash holdings after hurricane risk becomes salient for them. Our findings exhibit some of the traits associated with this type of salience related to geographical exposures, but are different in three key ways.

The first difference is that the salience in our setting is topically unique to climate change. That contrasts with the general salience to large recent disasters, which are more broadly established in Dessaint and Matray (2017). This feature is formalized in *Hypothesis 3* in section 2. As we note in that hypothesis, if the pricing effects captured by our specifications truly reflect the impact of climate change, the occurrence of *non-climate change-related disasters* should not lead to adjusted prices in at-risk borrowers' loan spreads. 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. To test this idea, Table 8 repeats the analysis from Table 2, but replaces our measures of direct and indirect exposure to hurricanes with analogous measures for earthquakes. One potential concern could be that the small numbers of earthquake strikes in the United States, as captured by the disaster frequencies during our sample period reported in Table 1, 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 8 here]

The coefficients of interest in Table 8 are those on the interaction term of $Indirect\ earthquake_{i,t} \times Recent\ earthquake_t$. In this particular set of tests, *Recent earthquake* takes the value of one if an earthquake is 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.

One potential concern in this table is 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 Internet Appendix Table IA.8, we show that we obtain similar null results when we define earthquake exposure using historic earthquake hits rather than seismic risk maps, or when we define the trigger for recent earthquakes using the thirteen most devastating global earthquakes (in terms of damages) during our sample period.[22] Again there is no effect on the risk premium charged for loans of at-risk U.S. firms in any specification. Finally, in Appendix Table IA.9, we find a similar null result for the effect of recent winter weather on spreads of indirectly affected firms. Our results are robust to using each disaster type individually as well as pooling climate change disasters and non–climate change disasters together.

Second, the economic agents for whom the hurricane is salient are very different across the two studies. In Dessaint and Matray (2017), the agents in question are executives who make decisions on corporate management. In contrast, the individuals that decide to adjust loan spreads are commercial bankers (e.g. Herpfer, 2021), and hence to trigger a similar salient overreaction, an event would need to take place geographically close to these *bankers*—not the firms' *CEOs*.

We obtain the location of bankers associated with the loans in our sample from Herpfer (2021) and identify bankers for whom a hurricane could be salient as those located in states that are directly hit by a hurricane in the

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

quarter of a loan.[23] If there is salience with respect to hurricanes similar to Dessaint and Matray (2017), bankers should react more strongly to these events by more steeply increasing the spreads charged to at-risk firms.

[Table 9 here]

In Table 9, we estimate this effect using a triple interaction between $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ and two measures of bankers' exposure to direct hurricanes: an indicator for any direct hurricane exposure in column 1, and a continuous measure of the damages caused by the hurricanes in the banker's state in column 2. In both tests, we find that our main coefficient on $Indirect\ hurricane \times Recent\ hurricane$ remains positive and statistically significant. Thus, after controlling for "geographic" salience at the banker level, banks still raise interest rates spreads by about 12 basis points to the exposed but unaffected borrowers. The coefficient estimates on the triple interaction terms are positive and economically large in both cases, but not statistically significant. It is plausible that there is indeed a degree of overreaction by local bankers with respect to local hurricanes, but the findings in Table 9 suggest that this is not the main driver of our result.

The last difference with Dessaint and Matray (2017) is that treated firms in that study are *headquartered* in areas that *are generally not at risk* of hurricanes: the neighboring but non-affected counties. In contrast, our study's setup explicitly isolates treated firms as those that *are generally at risk* of hurricanes. This means, by design, most treated firms in Dessaint and Matray (2017) cannot learn anything from a near miss, whereas the treated firms (and their lenders) in our paper potentially can learn from indirect hits. The placebo test in Internet Appendix Table IA.10 illustrates this key difference. We estimate an equation similar to equation (1), but follow Dessaint and Matray (2017) to define treated firms as $Indirect\ hurricane\ neighbour$. Unlike the coefficient on $Indirect\ hurricane \times Recent\ hurricane$ in our main tests, the coefficient on $Indirect\ hurricane\ neighbour \times Recent\ hurricane$ is insignificant and much smaller in magnitude.

In sum, our results are consistent with a salient reaction of bankers to natural disasters for firms at risk of these disasters. However, consistent with *Hypothesis 3*, this salience is unique to climate change-related natural disasters, which contrasts with the broad association of firm salience to tail events found in Dessaint and Matray (2017). Banker salience seems to be broader in the geographical context, as it not only impacts bankers that are geographically exposed to those disasters, but also bankers that are located in other areas.

[23] Banker data is only available up to 2013; hence our sample is smaller in these tests.

7 Additional robustness tests

We provide a wide range of additional robustness tests in the Internet Appendix. These include tests for alternative economic channels such as spillovers through geographic proximity in Internet Appendix Table IA.11, through customer-supplier networks in Internet Appendix Table IA.12, or spillovers through bank exposure in Internet Appendix Table IA.13. We also show the robustness of our results with respect to a wide range of sample compositions, including potential seasonality in the loan market that could overlap with the seasonality of disasters and to the inclusion of industry-times-time fixed effects, which shows that they are not driven by concurrent industry-wide shocks, in Internet Appendix Table IA.14. In another test, we rule out that any potential overlap between direct and indirect disaster hits drives our results in Internet Appendix Table IA.15. We further provide robustness tests with respect to a range of alternative ways of defining disaster exposure with varying intensity cutoffs in Internet Appendix Table IA.16, or measuring exposure based on employees rather than the number of establishments in Internet Appendix Table IA.17.

8 Effects on corporate policies

In our final set of tests, we investigate whether there are spillovers from banks' climate change-related adjustment in loan terms to corporate policies. Such spillovers are most plausible for firms that are most dependent on bank financing. Thus, we first identify these firms by using their lack of an investment-grade credit rating as in Table 5, which shows these firms indeed experience the largest increase in financing costs. We then 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. After saturating the models with firm- and year-fixed effects to draw inferences from changes in corporate decisions within the same firm over time, we present the results in Table 10. The outcome variables are the ratio of each firm's investments to its assets, and cash holdings as a fraction of liabilities.

[Table 10 here]

Consistent with CFOs realizing the risk of potential changes in financing costs and availability, columns 1 and 2 of Table 10 show 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. In columns 3 and 4, we investigate whether lower investment is accompanied by higher precautionary cash holdings. Again, consistent with firms that experience a worsening of credit conditions following an indirect hit becoming more cautious, 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, an economically large relative increase of 15% relative to the unconditional sample mean.[24]

These results are consistent with climate change-related disasters having an important effect on corporate investment and financial decisions. The most bank-dependent, indirectly-hit firms reduce their investments and increase their cash reserves, which is in line with these firms having to face potentially higher funding costs and lower credit access due to banks' adjustments of loan terms. Importantly, these effects are rather large and concentrated among borrowers that are more likely bank dependent.

9 Conclusion

We provide novel evidence showing that physical climate change-related risk through natural disasters affects corporate loan pricing. To disentangle the effect of direct disaster damage on loan pricing from updates in banks' expectations about the effect of climate change on natural 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. Banks charge these indirectly affected borrowers about 19 basis points more, or 10% compared to the unconditional loan spread. These effects are partially driven by a perceived increase in credit risk, which shows up in banks' internal PD assessments. However, a larger fraction of the increase in spreads is driven by bankers' salience associated with climate-related disasters. While banks react consistently to various types of disasters that are amplified by climate change, there are no reactions for disasters unrelated to climate change such as earthquakes. The spike in spreads is, however, short lived, but banks' overreaction causes real effects. Bank dependent firms that experience higher

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

spreads and lower loan amounts following an indirect hit subsequently reduce investments and increase cash holdings. There is, therefore, a spillover from banks' actions to corporate policies.

While we focus on whether physical risk affects borrowing costs for corporations through the link between bank lending and climate change-related natural disasters, many interesting questions remain for future research. First and foremost is the question of whether the lack of persistence of yield increases is missing the small increase in expected loan losses, that is, whether there is an initial overreaction followed by long term under-reaction, or whether the complete reversal of effects is correct. Another question is whether firms and banks shift their key operations away from regions affected by climate change-related disasters to mitigate the potential medium and long term effects of climate change.

References

Abatzoglou, J. T., Williams, A. P., 2016. Impact of anthropogenic climate change on wildfire across western us forests. Proceedings of the National Academy of Sciences 113, 11770–11775.

Afrouzi, H., Kwon, S. Y., Landier, A., Ma, Y., Thesmar, D., 2020. Overreaction in expectations: Evidence and theory. Working Paper .

Alok, S., Kumar, N., Wermers, R., 2020. Do fund managers misestimate climatic disaster risk. The Review of Financial Studies 33, 1146–1183.

Baldauf, M., Garlappi, L., Yannelis, C., 2020. Does climate change affect real estate prices? only if you believe in it. Review of Financial Studies 33, 1256–1295.

Bank of England, 2022. Climate capital. Speech by Deputy Governor Sam Woods at a webcast hosted by the Global Association of Risk Professionals, May 24.

Barrot, J.-N., Sauvagnat, J., 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. Quarterly Journal of Economics 131, 1543–1592.

Bender, M. A., Knutson, T. R., Tuleya, R. E., Sirutis, J. J., Vecchi, G. A., Garner, S. T., Held, I. M., 2010. Modeled impact of anthropogenic warming on the frequency of intense atlantic hurricanes. Science 327, 454–458.

Berger, A. N., Curti, F., Lazaryan, N., Mihov, A., Roman, R. A., 2022. Climate risks in the US banking sector: Evidence from operational losses and extreme storms. Working Paper .

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

Blickle, K., Hamerling, S. N., Morgan, D. P., 2021. How bad are weather disasters for banks? FRB of New York Staff Report .

Christensen, J. H. E., 2007. Internal risk models and the estimation of default probabilities. FRBSF Economic Letter .

Cortés, K. R., Strahan, P. E., 2017. Tracing out capital flows: How financially integrated banks respond to natural disasters. Journal of Financial Economics 125, 182–199.

Delis, M., De Greiff, K., Ongena, S., 2018. Being stranded on the carbon bubble? climate policy risk and the pricing of bank loans. SFI Research Paper .

Dell, M., Jones, B. F., Olken, B. A., 2014. What do we learn from the weather? the new climate-economy literature. Journal of Economic Literature 52, 740–98.

Dessaint, O., Matray, A., 2017. Do managers overreact to salient risks? evidence from hurricane strikes. Journal of Financial Economics 126, 97–121.

Elsner, J. B., Jagger, T. H., et al., 2009. Hurricanes and climate change. Springer.

Engle, R., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2021. Hedging climate change news. Review of Financial Studies, forthcoming .

European Central Bank and European Systemic Risk Board, 2022. The macroeconomic challenge of climate change. ECB-ESRB Project Team on climate risk monitoring, July.

Financial Stability Board, 2020. The Implications of Climate Change for Financial Stability.

Gensini, V. A., Brooks, H. E., 2018. Spatial trends in united states tornado frequency. NPJ Climate and Atmospheric Science 1, 1–5.

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., Weber, A., 2021. Climate change and long-run discount rates: Evidence from real estate. The Review of Financial Studies 34, 3527–3571.

Giglio, S., Maggiori, M., Stroebel, J., 2015. Very long-run discount rates. Quarterly Journal of Economics 130, 1–53.

Gillett, N., Weaver, A., Zwiers, F., Flannigan, M., 2004. Detecting the effect of climate change on canadian forest fires. Geophysical Research Letters 31.

Goldsmith-Pinkham, P. S., Gustafson, M., Lewis, R., Schwert, M., 2019. Sea level rise and municipal bond yields. Working paper .

Grinsted, A., Ditlevsen, P., Christensen, J. H., 2019. Normalized us hurricane damage estimates using area of total destruction, 1900- 2018. Proceedings of the National Academy of Sciences 116, 23942–23946.

He, A., 2019. Spillovers of natural disaster strikes through bank-firm networks: loan- and firm-level evidence of financial constraints. Working paper .

Herpfer, C., 2021. The role of bankers in the us syndicated loan market. Journal of Accounting and Economics 71, 101383.

Hong, H., Karolyi, G. A., Scheinkman, J. A., 2020. Climate Finance. The Review of Financial Studies 33, 1011–1023.

Huang, Q., Jiang, F., Xuan, Y., Yuan, T., 2022. Do banks overreact to disaster risk? Working Paper .

Ivanov, I., Kruttli, M. S., Watugala, S. W., 2020. Banking on carbon: Corporate lending and cap-and-trade policy. Working paper .

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263–291.

Klibanoff, P., Lamont, O., Wizman, T. A., 1998. Investor reaction to salient news in closed-end country funds. The Journal of Finance 53, 673–699.

Knutson, T., Camargo, S. J., Chan, J. C. L., Emanuel, K., Ho, C.-H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K., Wu, L., 2019. Tropical cyclones and climate change assessment: Part i: Detection and attribution. Bulletin of the American Meteorological Society 100, 1987 – 2007.

Koetter, M., Noth, F., Rehbein, O., 2020. Borrowers under water! Rare disasters, regional banks, and recovery lending. Journal of Financial Intermediation 43, 100811.

Kossin, J. P., Knapp, K. R., Olander, T. L., Velden, C. S., 2020. Global increase in major tropical cyclone exceedance probability over the past four decades. Proceedings of the National Academy of Sciences 117, 11975–11980.

Krueger, P., Sautner, Z., Starks, L. T., 2020. The importance of climate risks for institutional investors. Review of Financial Studies 33, 1067–1111.

Kruttli, M., Roth Tran, B., Watugala, S. W., 2019. Pricing poseidon: extreme weather uncertainty and firm return dynamics. FEDS Working Paper .

Lee, S. J., Li, D., Meisenzahl, R. R., Sicilian, M., 2019. The U.S. Syndicated Term Loan Market: Who Holds What and When? FEDS Notes 2019-11-25, Board of Governors of the Federal Reserve System (U.S.).

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J., Maycock, T., Waterfield, T., Yelekçi, O., Yu, R., Zhou, B., 2021. Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change .

Mendelsohn, R. O., Saher, G., 2011. The global impact of climate change on extreme events. Working Paper 5566, World Bank .

Murfin, J., Petersen, M., 2016. Loans on sale: Credit market seasonality, borrower need, and lender rents. Journal of Financial Economics 121, 300–326.

Murfin, J., Spiegel, M., 2020a. Is the risk of sea level rise capitalized in residential real estate? Review of Financial Studies 33, 1217–1255.

Murfin, J., Spiegel, M., 2020b. Is the risk of sea level rise capitalized in residential real estate? The Review of Financial Studies 33, 1217–1255.

Nordhaus, W. D., 2010. The economics of hurricanes and implications of global warming. Climate Change Economics 1, 1–20.

Painter, M., 2020. An inconvenient cost: The effects of climate change on municipal bonds. Journal of Financial Economics 135, 468–482.

Pielke Jr, R. A., Gratz, J., Landsea, C. W., Collins, D., Saunders, M. A., Musulin, R., 2008. Normalized hurricane damage in the united states: 1900–2005. Natural Hazards Review 9, 29–42.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., Ziegler, A., 2019. Investor rewards to climate responsibility: Evidence from the 2016 climate policy shock. NBER Working Paper 25310 .

Risser, M. D., Wehner, M. F., 2017. Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation during hurricane harvey. Geophysical Research Letters 44, 12–457.

Sautner, Z., van Lent, L., Vilkov, G., Zhang, R., 2022a. Firm-level climate change exposure. Journal of Finance .

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2022b. Pricing climate change exposure. Management Science .

Schüwer, U., Lambert, C., Noth, F., 2019. How Do Banks React to Catastrophic Events? Evidence from Hurricane Katrina. Review of Finance 23, 75–116.

Seltzer, L. H., Starks, L., Zhu, Q., 2022. Climate regulatory risk and corporate bonds .

Seneviratne, S. I., Nicholls, N., Easterling, D., Goodess, C. M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., et al., 2017. Changes in climate extremes and their impacts on the natural physical environment .

Smith, A. B., Katz, R. W., 2013. Us billion-dollar weather and climate disasters: data sources, trends, accuracy and biases. Natural Hazards 67, 387–410.

Stern, N., 2007. The economics of climate change: the Stern review. Cambridge University Press.

Van Der Wiel, K., Kapnick, S. B., Van Oldenborgh, G. J., Whan, K., Philip, S., Vecchi, G. A., Singh, R. K., Arrighi, J., Cullen, H., 2017. Rapid attribution of the august 2016 flood-inducing extreme precipitation in south louisiana to climate change. Hydrology and Earth System Science 21, 897–921.

Van Oldenborgh, G. J., Van Der Wiel, K., Sebastian, A., Singh, R., Arrighi, J., Otto, F., Haustein, K., Li, S., Vecchi, G., Cullen, H., 2017. Attribution of extreme rainfall from hurricane harvey, august 2017. Environmental Research Letters 12, 124009.

Weitzman, M. L., 2009. On modeling and interpreting the economics of catastrophic climate change. Review of Economics and Statistics 91, 1–19.

Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., Lettenmaier, D. P., 2019. Observed impacts of anthropogenic climate change on wildfire in california. Earth's Future 7, 892–910.

Wuebbles, D. J., Fahey, D. W., Hibbard, K. A., Arnold, J. R., DeAngelo, B., Doherty, S., Easterling, D. R., Edmonds, J., Edmonds, T., Hall, T., et al., 2017. Climate science special report: Fourth national climate assessment, volume i .

Figures

Figure 1: Geographic hurricane exposure in 2008
This figure presents county level hurricane exposure in 2008 based on the total damage (in $million) caused by previous 10 years' hits from SHELDUS.

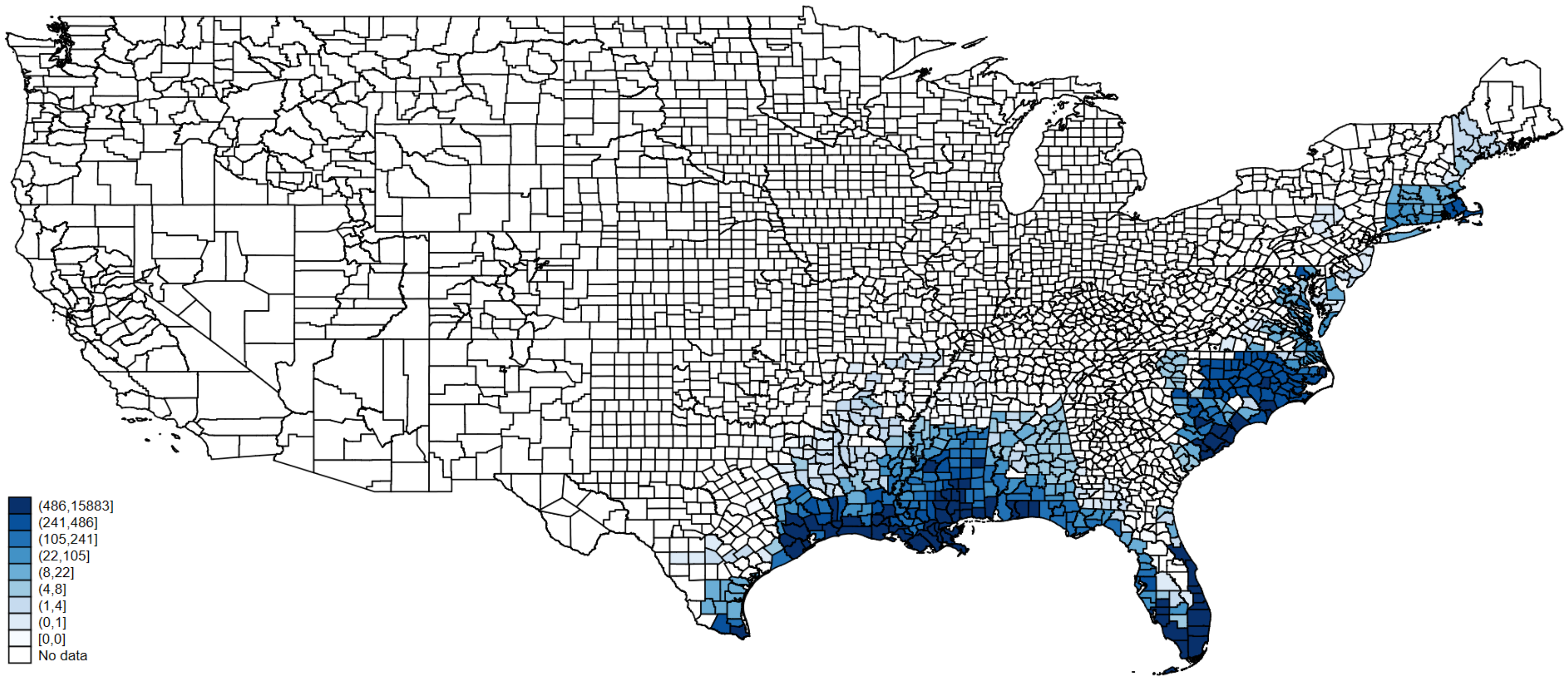


Figure 2: Geographic seismic ground motion assessment in 2008
This figure presents county level earthquake exposure in 2008 based on the ground motion assessments of the U.S. Geological Survey (USGS).

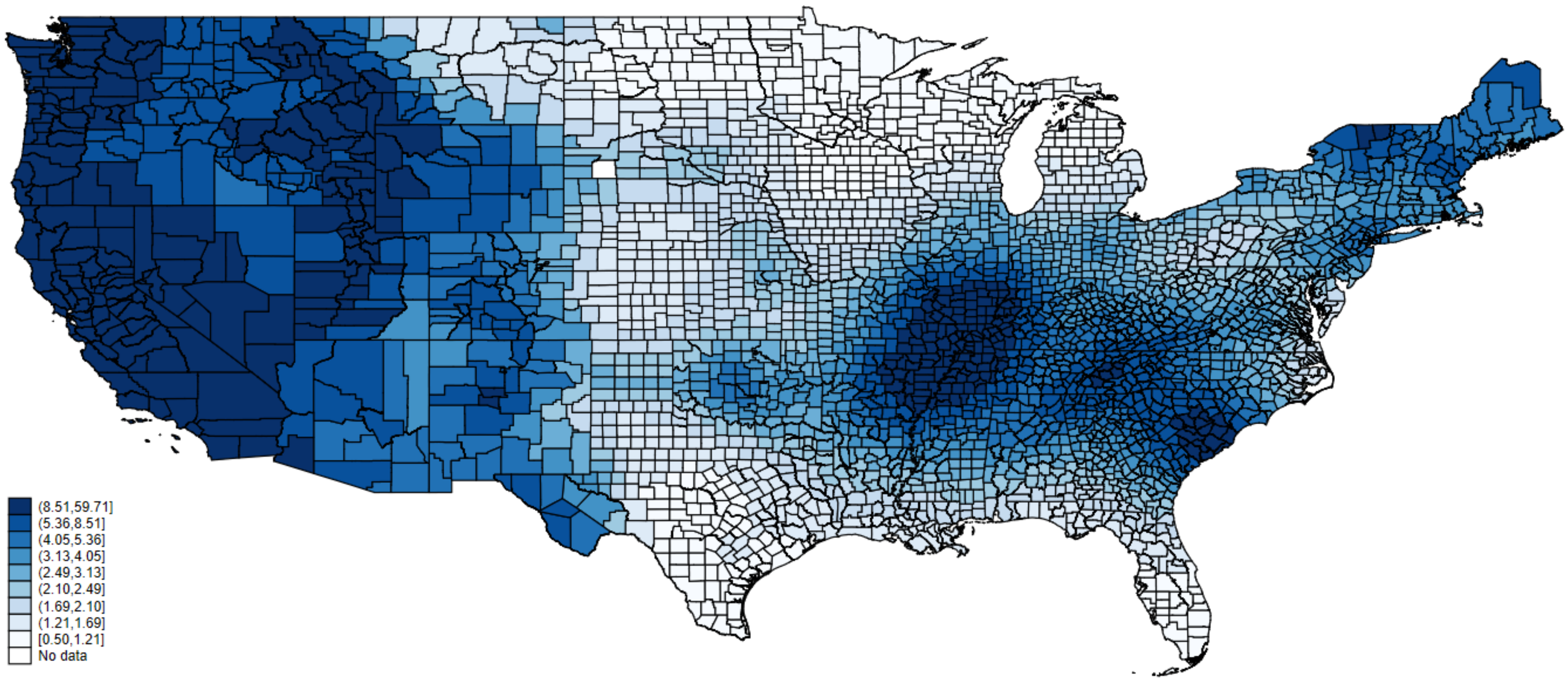


Figure 3: The effect of direct exposure to climate change-related disasters on loan spreads over time
This figure presents the effect of direct exposure to climate change-related disasters on loan spreads over time. Climate change-related disasters are defined as hurricanes, wildfires and floods. Direct 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 2000 form the base period.

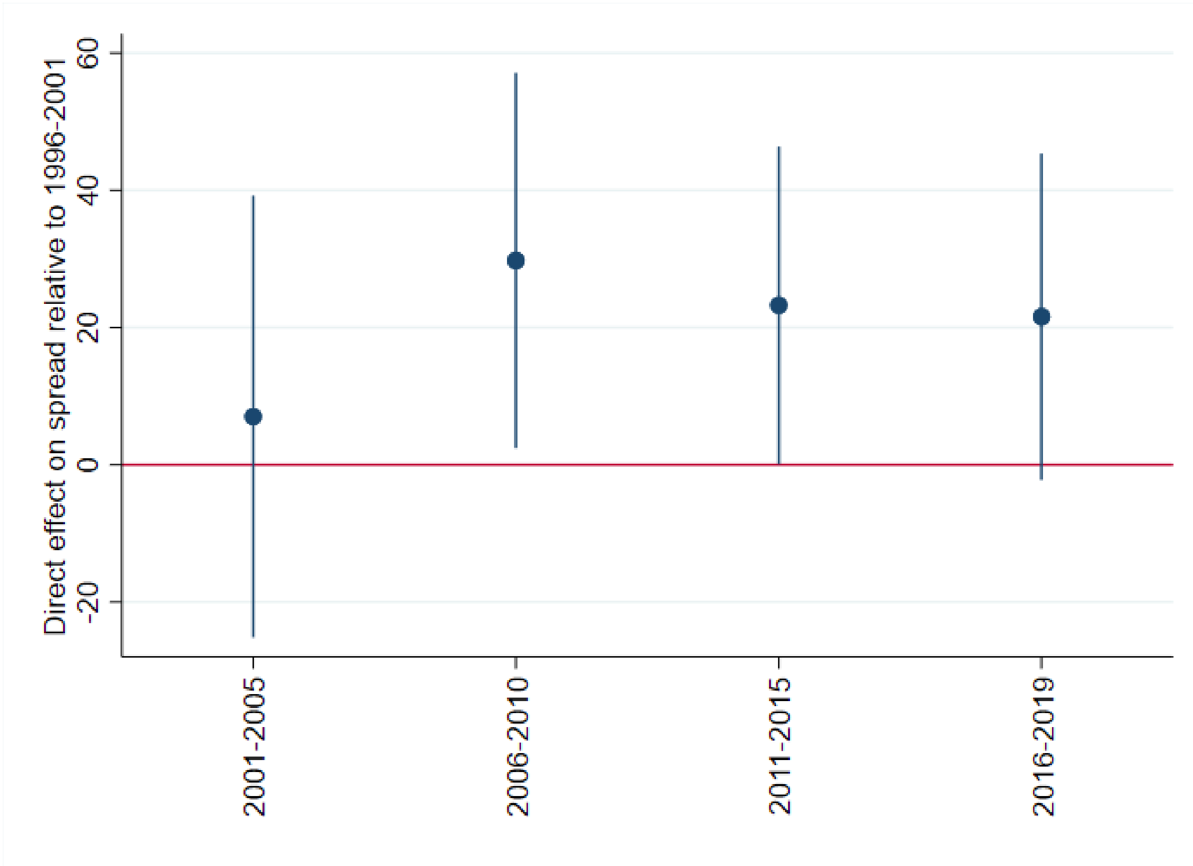


Figure 4: Dynamics of spread reaction in the primary market
This figure presents the dynamics of effects of indirect hits from climate change-related disasters on loan spreads over time. Climate change-related disasters are defined as hurricanes. Indirect hits are defined as in our main specification. The plot shows estimated coefficients, $\beta_{1,\tau}$, of the following regression performed in the main sample of Table 2:

$$Spread_{i,m,t} = \sum_{\tau=-2}^{4} (\beta_{1,\tau} Indirect\ hurricane_{i,t} \times Recent\ hurricane_{t+\tau} + \beta_{3,\tau} Recent\ hurricane_{t+\tau}) + \beta_2 Indirect\ hurricane_{i,t} + \gamma X_{i,m,t} + \alpha_i + \phi_{m,y} + \epsilon_{i,m,t}, \quad (2)$$

where $Recent\ hurricane_{t-\tau}$ are indicators for occurrences of a hurricane from two quarters prior ($\tau = -2$) to four quarters after ($\tau = 4$) the loan was issued. Other variables are the same with the ones in Equation (1). Vertical lines represent 90% confidence intervals clustered by borrower and year.

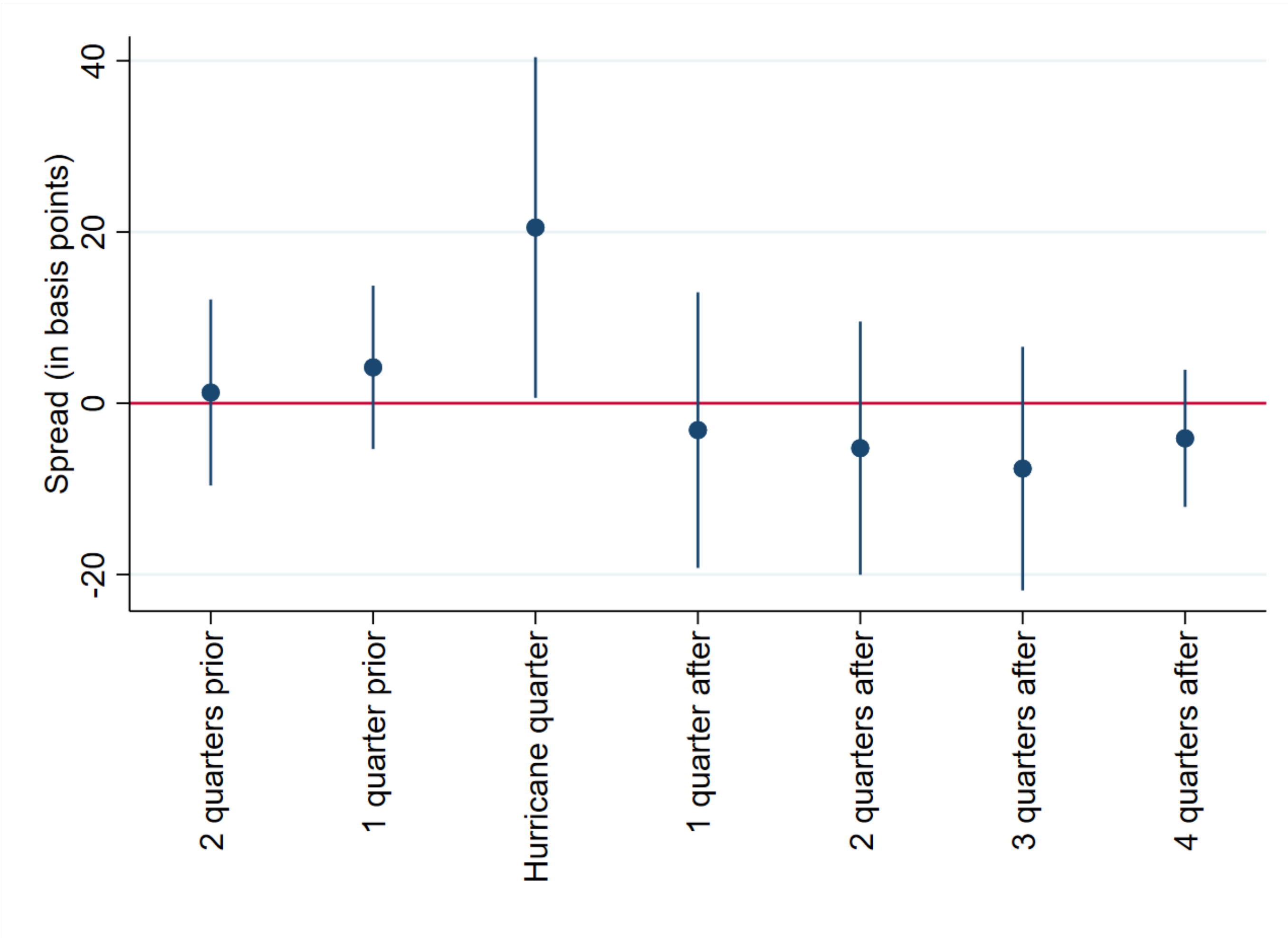
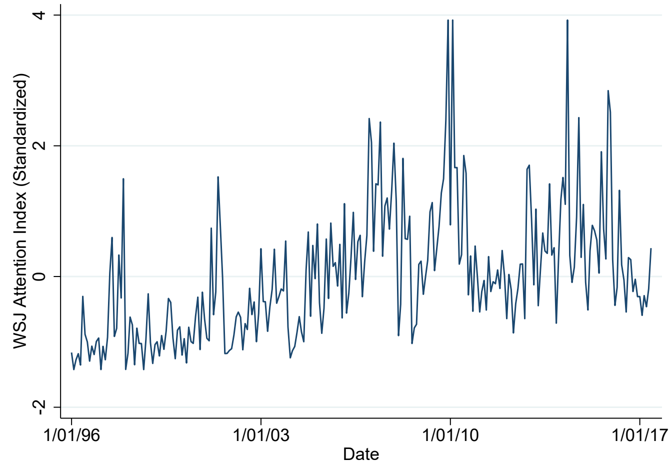
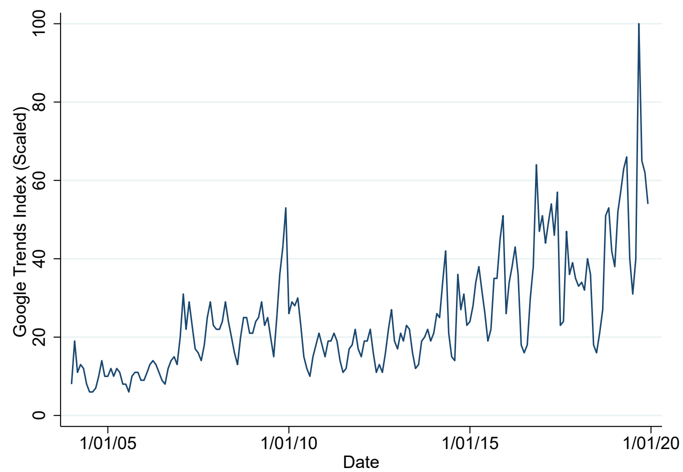


Figure 5: Attention indexes for climate change and natural disasters

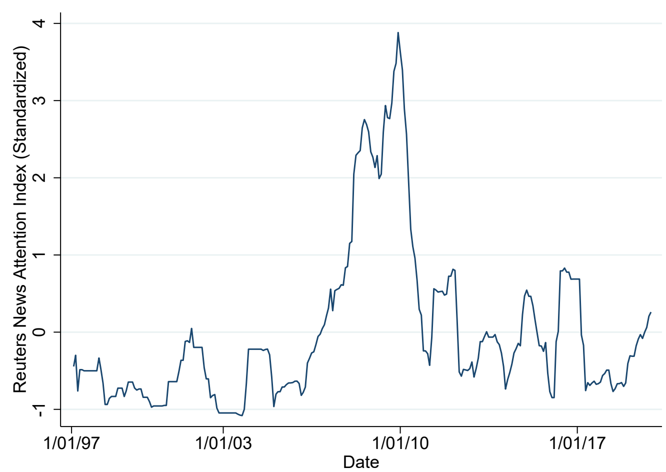
This figure presents three different climate change attention indexes. (a) is the standardized Wall Street Journal climate change news index of Engle et al. (2021), from 1996/01 to 2017/06. (b) is the Google search volume of "climate change", scaled by taking the maximum value as 100, from 2004/01 to 2019/12. (c) is a standardized news index based on the ratio of articles from Reuters News mentioning a connection between storms and climate change among all articles mentioning storms, from 1997/01 to 2019/12.



Panel A: Wall Street Journal climate change news index



Panel B: Google search trends



Panel C: Reuters News attention index

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 major hurricanes. 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 C reports summary statistics for the daily quote price of loans in the secondary market from 2000 to 2017, and the PDs reported by banks in their FR Y-14Q filings from 2014 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 (dummy)	21262	0.22	0.36	0.00	0.00	0.42
Revolving loan (dummy)	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: The secondary loan market and bank internal data

	N	Mean	Std Dev	min	p50	max
Daily quote price	62085	95.83	57.53	0.20	98.64	3800
Probability of default	43008	0.01	0.05	0.00	0.0025	1

Table 2: Interest rate spreads and climate change-related disasters
This table presents results from regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three 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 are 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

Table 3: Pricing of climate change-related disasters in the secondary market

This table reports regressions of the log of daily average quote prices in the loan secondary market on the interaction of borrowers' indirect hurricane risk indicator with the occurrence of hurricanes in the preceding four weeks. The sample includes existing loans' daily average 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 are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Log Quote			
	(1)	(2)	(3)	(4)
Indirect hurricane × *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 4: Banks' internal assessment of climate change
This table reports regressions of banks' assessments of default probabilities on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three 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 are 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 5: Pricing of climate change-related disasters across borrowers

This table reports regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three 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). We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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 are 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
Lower interactions	Yes	Yes	Yes

Table 6: Time-varying attention to climate change
This table reports regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three 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. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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 are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1)	(2)	(3)
$Indirect\ hurricane \times Recent\ hurricane$	16.603*	-13.047	-44.620***
	(8.360)	(13.647)	(14.984)
$Indirect\ hurricane \times Recent\ hurricane \times WSJ\ index$	41.659**		
	(17.006)		
$Indirect\ hurricane \times Recent\ hurricane \times Above\ median\ attention$		47.982**	
		(17.392)	
$Indirect\ hurricane \times Recent\ hurricane \times Medium\ tercile\ attention$			66.370***
			(18.420)
$Indirect\ hurricane \times Recent\ hurricane \times Top\ tercile\ attention$			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
Lower interactions	Yes	Yes	Yes

Table 7: Cross-sectional attention to climate change

This table reports regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. *Bank* (*discuss cc risk*) and *Bank* (*discuss cc exposure*) indicate, respectively, that a bank discusses climate-change risk or exposure in the earnings call meeting right after the hurricane hit. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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 are 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*	18.418	18.816	8.261	10.677
	(11.185)	(11.645)	(11.484)	(12.496)
Indirect hurricane × *Recent hurricane* × *Bank*(*discuss cc risk*)	71.515**	65.877*		
	(33.066)	(37.493)		
Indirect hurricane × *Recent hurricane* × *Bank*(*discuss cc exposure*)			25.758**	21.486*
			(12.683)	(13.005)
N	12808	12808	12808	12808
R^2	0.682	0.726	0.682	0.726
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
Lower interactions	Yes	Yes	Yes	Yes

Table 8: Placebo test: interest rate spreads and non-climate change-related disasters

This table reports regressions of loan spread (in basis points) on the interaction of borrowers' indirect earthquake exposure indicator with the occurrence of a major earthquake in the preceding three months. The indirect earthquake exposure is constructed based on each firm's location-weighted seismic hazard ground motion from USGS 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 are 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 9: Salience at the banker level

This table reports regressions of loan spread on the interaction of borrowers' indirect hurricane exposure, an indicator that captures the occurrence of a major hurricane in the preceding three months, and a third interaction term *Banker direct hurricane*, which captures whether the banker is located in a state that has a direct hurricane hit in the quarter of the loan, and is hence subject to potential salience. In column 2, the triple interaction is with *Banker hurricane severity*, the damages ($ million) caused by hurricanes in the state of the banker. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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. Banker data is from Herpfer (2021). 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)
Indirect hurricane × *Recent hurricane*	11.779**	11.901**
	(4.749)	(4.767)
Indirect hurricane × *Recent hurricane* × *Banker direct hurricane*	17.804	
	(41.212)	
Indirect hurricane × *Recent hurricane* × *Banker hurricane severity*		0.055
		(0.090)
N	16554	16554
R^2	0.782	0.782
Bank × Year FE	Yes	Yes
Firm FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
Lower interactions	Yes	Yes

Table 10: Corporate finance effects of climate change risk
This table reports regressions of firms' annual investment ratio and cash ratio on the interaction of their indirect hurricane exposure indicator with the occurrence of a major hurricane in the previous year. *Non-investment grade* is an indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB). We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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 are 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 × *Recent hurricane*	0.233	0.304	-5.344	-5.708
	(0.199)	(0.213)	(3.340)	(3.336)
Indirect hurricane × *Recent hurricane*×*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
Lower interactions	Yes	Yes	Yes	Yes

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

A.1 Variable Definitions

Loan Variables	
Financial covenant	Indicator equal to one if the loan contract includes covenants
Loan amount	Loan amount in dollars, adjusted to 2019 values
Maturity	The number of years between loan start and end dates
Number of financial covenants	The number of covenants in a loan contract
Revolving loan	Indicator equal to one if the loan type is revolver
Spread	The all-in-drawn spread in basis points
Term loan	Indicator equal to one if the loan type is term loan
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 annual total footprints in hurricane-prone counties. A hurricane-prone county in month t is the one which, in the past 120 months, 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 three months.
Recent earthquake$_t$	A time indicator equal to one if an earthquake hit during the preceding three months.
Other Variables	
Banker direct hurricane	Indicator equal to one if a loan's banker is located in a state that has a direct hurricane hit in the quarter of the loan origination.

Bank (discuss cc risk)	Indicator equal to one if a bank discusses its climate-change risk in the earnings call meeting right after a hurricane hit.
Bank (discuss cc exposure)	Indicator equal to one if a bank discusses its climate-change exposure in the earnings call meeting right after a hurricane hit.
Banker hurricane severity	The damages ($ million) caused by hurricanes in the state of the banker in the quarter of the loan origination.
CapEx/Assets	Borrower annual physical capital expenditure (PP&E) over assets.
Cash/Liabilities	Borrower annual cash divided by current liabilities.
Market leverage	The normalized value of firms' market leverage ratio.
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.
WSJ index	The Wall Street Journal climate change news index, a standardized attention index constructed in Engle et al. (2021).

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

Ricardo Correa, Ai He, Christoph Herpfer and Ugur Lel

IA.1 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 IA.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 IA.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 wildfires, 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.**"

IA.2 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 wildfires 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 IA.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.

These exercises demonstrate 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.[25]

[25]In separate results, as an alternative, we directly 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"*).

IA.3 Internet appendix tables

Table IA.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 IA.2: Floods 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 three 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 IA.3: 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 three 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 IA.4: Other loan terms

This table reports regressions of other loan terms on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. The outcomes in Columns 1 to 4 are the natural logarithm of the loan amount, the natural logarithm of loan maturity, an indicator for whether a loan is a revolver (as opposed to a term loan) and an indicator for the presence of financial covenants, respectively. 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. Banker data is from Herpfer (2021). 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.

	Log(amount)	Log(maturity)	Revolver	Covenant
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	-0.209*	-0.105	0.027	-0.057
	(0.114)	(0.072)	(0.038)	(0.060)
Indirect hurricane	0.109**	-0.036	-0.004	-0.017
	(0.045)	(0.025)	(0.017)	(0.025)
Recent hurricane	0.018	0.015	-0.046***	0.035
	(0.045)	(0.019)	(0.013)	(0.021)
N	21262	21262	21262	21262
R^2	0.782	0.577	0.540	0.539
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 IA.5: 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 three 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. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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.

	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
Lower interactions	Yes	Yes	Yes

Table IA.6: 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 three 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. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. 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.

	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
Lower interactions	Yes	Yes	Yes

Table IA.7: Pricing of climate change-related disasters with different characteristics

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 three months. $Recent\ hurricane_{>\$100bn}$, $Recent\ hurricane_{total\ hit\ counties\ top\ 1\%\ ever}$, and $Recent\ hurricane_{total\ first\ hit\ counties\ top\ 1\%\ ever}$ indicate the hurricane as "novel", respectively, signalling by the total losses exceeding $100 billion, the total number of counties hit is in top 1% ever, or the total number of counties which are first hit by a hurricane is in top 1% ever. 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*		
	(15.993)		
$Indirect\ hurricane \times Recent\ hurricane_{total\ hit\ counties\ top\ 1\%\ ever}$		77.734***	
		(27.378)	
$Indirect\ hurricane \times Recent\ hurricane_{total\ first\ hit\ counties\ top\ 1\%\ ever}$			62.991**
			(29.260)
Indirect hurricane	4.292*	4.291*	4.337*
	(2.288)	(2.287)	(2.296)
$Recent\ hurricane_{>\$100bn}$	-0.390		
	(4.453)		
$Recent\ hurricane_{total\ hit\ counties\ top\ 1\%\ ever}$		-1.676	
		(6.209)	
$Recent\ hurricane_{total\ first\ hit\ counties\ top\ 1\%\ ever}$			6.966
			(6.145)
N	21262	21262	21262
R^2	0.742	0.742	0.742
Bank × Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table IA.8: 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 8. The indicator *Recent earthquake* is also defined as in Table 8 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 IA.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 three 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 IA.10: Placebo tests with neighboring counties

This table reports results of placebo tests with other variables being the same with the ones in Table 2, except for *Indirect hurricane neighbour*. To construct *Indirect hurricane neighbour*, we follow Dessaint and Matray (2017) to use hurricane-unaffected but neighboring counties. Analogous to our main specification, *Indirect hurricane neighbour* is to identify a firm if it is in the top quintile ranked by the location-weighted exposure in these *neighboring* counties.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane neighbor × *Recent hurricane*	4.594	2.705	5.230	4.612
	(7.998)	(9.111)	(8.695)	(8.746)
Indirect hurricane neighbor	-0.144	2.065	1.232	1.366
	(3.985)	(3.954)	(3.836)	(3.850)
Recent hurricane	5.098	2.708	2.715	3.084
	(4.156)	(4.127)	(3.830)	(3.817)
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

Table IA.11: Regional spillovers from neighbouring counties
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 three months. *Operations neighbour counties* is a firm's total footprints in the unaffected counties that are neighbours of the hurricane. 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*	17.208**	18.715**	19.130**	18.752**
	(7.738)	(8.377)	(8.622)	(8.487)
Indirect hurricane	3.049	3.136	3.552	3.480
	(5.047)	(4.404)	(4.028)	(3.975)
Recent hurricane	3.063	0.308	0.706	1.037
	(3.874)	(3.808)	(3.671)	(3.685)
Operations neighbour counties × *Recent hurricane*	21.369	11.583	9.027	8.416
	(15.964)	(15.495)	(14.048)	(14.793)
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

,

Table IA.12: Borrowers' economic links and interest rate spreads

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last three 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 the 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 IA.13: 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 three 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 IA.14: 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.

	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-Season 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 IA.15: 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 IA.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 three 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.

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane general × *Recent hurricane*	18.772*			
	(9.550)			
Indirect hurricane general continuous × *Recent hurricane*		4.536**		
		(2.020)		
Indirect hurricane continuous × *Recent hurricane*			4.751**	
			(2.066)	
Any indirect hurricane × *Recent hurricane*				17.142**
				(7.152)
N	21262	21262	21262	21262
R^2	0.743	0.742	0.742	0.742
Bank × 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 IA.17: 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.

	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

about ECGI

The European Corporate Governance Institute has been established to improve *corporate governance through fostering independent scientific research and related activities.*

The ECGI will produce and disseminate high quality research while remaining close to the concerns and interests of corporate, financial and public policy makers. It will draw on the expertise of scholars from numerous countries and bring together a critical mass of expertise and interest to bear on this important subject.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

Electronic Access to the Working Paper Series

The full set of ECGI working papers can be accessed through the Institute's Web-site (www.ecgi.global/content/working-papers) or SSRN:

Finance Paper Series	http://www.ssrn.com/link/ECGI-Fin.html
Law Paper Series	http://www.ssrn.com/link/ECGI-Law.html