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

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Abstract

We investigate how corporate loan costs are affected by climate change-related natural disasters. We construct granular measures of borrowers' exposure to natural disasters and then disentangle the direct effects of disasters from the effects of lenders updating their beliefs about the impact of future disasters. Following a climate change-related disaster, spreads on loans of at-risk, yet unaffected borrowers, spike and are amplified when attention to climate change is high. Weaker borrowers with the most extreme exposure to these disasters suffer the highest increase in spreads. Importantly, there is no such effect from disasters that are not aggravated by climate change.

JEL Classifications: G21, Q51, Q54

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

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1 Introduction

Climate change can have potentially devastating long-term economic effects (Stern, 2007), with the majority of the consequences of climate change expected towards the end of the century (Hong, Karolyi, and Scheinkman, 2020). However, the long delay before these effects fully impact the global economy can discourage actions to mitigate climate change-related risks, and the relevance of these risks from today's perspective depends heavily on discount rates (Nordhaus, 2010). As a result, large parts of the literature on climate change and financial markets have concentrated on long-lived assets such as real estate or equities (Giglio, Maggiori, and Stroebel, 2015; Bernstein, Gustafson, and Lewis, 2019; Murfin and Spiegel, 2020; Baldauf, Garlappi, and Yannelis, 2020), with an emphasis on estimating discount rates to capture long-run damages (Giglio, Maggiori, Rao, Stroebel, and Weber, 2018). Our paper investigates a novel channel by which climate change already shapes economic risks today, that is, through the increased frequency and severity of certain extreme weather events. With regulators and central banks increasingly worried about potential systemic risks from climate change, it is crucial to answer whether loan market participants and banks are aware of and price climate change risk.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

[3]As presented in Internet Appendix Table IA.1, banks had started to note natural disasters as an important risk by 2010. In 2019, all banks in the sample flag those disasters as a material issue and linked them to climate change. For example, PNC Bank's 2019 10-K filing explicitly states, "Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans." Internet Appendix section IA.1 provides a wide range of examples for this type of awareness of the link between climate change, disasters, and credit risk.

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

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

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

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

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

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

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

Another contribution is that we provide estimates on the credit risk that banks assign to natural disasters related to climate change. This assessment is crucial, as banks will be incentivized to enhance their risk-management practices related to climate risks if severe weather incidents become more intense and more frequent as predicted. In a related manner, the finding that loan spread hikes around climate change-related natural disasters are transitory and driven significantly by attention to climate risks may have consequences from a regulatory perspective. For example, if banks do not adjust their risk assessments associated to these types of disasters, they could inadequately provision for potential future climate change-related loan losses, and this could diminish their financial resilience and result in economy-wide adverse effects in the future.

2 Hypotheses development

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

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

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

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

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

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

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

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

3 Data

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

3.1 Data on disasters

We obtain data on disasters from SHELDUS, which is a county-level natural hazard data set for the United States. It encompasses information from 1960 to the present. This database provides information on the type of hazard, affected location (county and state), year and month, and the direct losses caused by the hazard (e.g., property and crop losses, injuries, and fatalities). These data are widely used in studies on the effect of natural disasters, including studies on bank lending (Cortés and Strahan, 2017). Our data captures disasters in which the Governor of a state declares a "state of emergency" with a formal request for Federal Emergency Management Agency (FEMA) funds to respond to the disaster. Thus, we include only relatively large disasters. We then classify disasters as being related to climate change based on reports produced by the IPCC (Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi, et al., 2017).[5] These reports find substantial evidence of a link between climate change, heat waves, and wildfires. The report finds similarly strong evidence for a link between climate change and more severe Atlantic hurricanes as well as extreme precipitation. Therefore, we classify hurricanes, floods, and wildfires as climate change related severe weather events.

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

In our baseline specification, we focus on hurricanes as climate change-related disasters, as 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 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 Internet Appendix section IA.3, we show that our results hold for a set of climate-related disasters, beyond hurricanes, individually as well as in a pooled estimation of them jointly.

We contrast our findings for climate change-related disasters with those that are unrelated to climate change. Among natural disasters, earthquakes are the most clearly unrelated to climate change. Therefore, our main specification uses earthquakes as non–climate change disasters. Since earthquakes are rather infrequent in the U.S. and there have been few in the SHELDUS data, we use seismic hazard site-specific data from the U.S. Geological Survey (USGS) from the Department of the Interior to capture the likelihood that specific locations could be affected by this type of natural disaster. [6] Starting in 1996, the data project potential maximum expected ground motions of latitude/longitude locations across the conterminous United States. These data allow us to construct a detailed county-level assessment of exposures to earthquake hazards. As with the climate change-related disasters, we use the SHELDUS data to capture the realization of earthquakes in the United States. However, given the sparsity of these natural disasters as mentioned previously, we also run an additional robustness test using foreign earthquakes as shocks to attention to earthquakes.

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

Figure 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, roughly 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 south east and the Atlantic coast, while seismic ground motions are most active along the west coastal line.

[6]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.

[Figure 1 here]

[Figure 2 here]

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

3.2 Data on firm and bank exposures to natural disasters

After we measure each county's exposure to natural disasters, we next construct granular corporate geographic footprints to quantify each borrower's exposure to climate change–related disasters. Deutsche Bank, in its 2018 white paper, captures this intuition: "Perhaps the most telling metric of a company's climate risk is the location of its assets and their exposure to changing extreme weather patterns. The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks."[7] 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, van Lent, Vilkov, and Zhang, 2020; Sautner, Van Lent, Vilkov, and Zhang, 2021).

We construct detailed geographic footprints of corporations using the NETS dataset from Walls and Associates.[8] We use information at the county-level that captures the number of establishments that a firm has in a given location to create a location-weighted measure of a company's exposure to each disaster type. To do so, we multiply each firm's fraction of establishments in each county by that county's exposure to disasters, arriving at an operations-weighted measure of a firm's exposure to disasters. We then classify a firm as *indirectly exposed* to each type of disaster (e.g., hurricanes) if its operations-weighted exposure to historically disaster-prone counties

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

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

is in the top quintile of firms.[9] For earthquake exposure, besides measured by historical occurrence based on the SHELDUS data, we also apply each firm's location-weighted ground motion assessment.

In the last layer of our dataset, we add syndicated loan data from Refinitiv's DealScan database and balance sheet and income statement data for firms from S&P Compustat. DealScan provides loan information at origination, including loan amount, loan maturity, and loan spread. We begin our sample in 1996 with the introduction of the SEC's mandatory electronic filing. We include all loans originated in the United States that can be matched with borrowers that appear in the NETS dataset. We use loan amounts in 2019 dollars, adjusting the nominal value using the GDP-deflator produced by the Bureau of Economic Analysis. Syndicated loans have one or more lead arrangers and several participating lenders. A lead arranger serves as an administrative agent who has a fiduciary duty to other syndicate members to provide timely information about the borrower, whereas participating lenders are passive investors whose main role is sharing the ownership of a loan. In our empirical tests, we restrict our analysis to lead arrangers. On the borrower side, firms that borrow through syndicated loan arrangements can potentially be directly and indirectly affected by a disaster at a point in time. To avoid our results from being polluted by any potential direct effect of natural disasters, we exclude all loans of those borrowers that have suffered from either hurricanes or earthquakes within 3 months of the loan origination.

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

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

after the end of 2014, which restricts our sample to the period between 2014 and 2019.[10]

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

[Table 1 here]

Panel A covers all matched loans in our main test sample. The median loan is a $649.73 million (in 2019 U.S. dollar) credit package with a 5-year maturity and a 150.00 basis points credit spread. More than half of the loans have financial covenants, and around three-fourths of the loans are revolving credit facilities. The median borrower in the sample has $3.60 billion in total assets, with a return on asset (ROA) of 0.12 and a debt-to-asset ratio of 0.33. About 10% of the loans are originated within three months after a hurricane hit. Similarly, about 4% of the loans are originated within three months after an earthquake strike.

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

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

4 Climate change and loan pricing

4.1 Empirical setup

As described in section 2, our main objective is to test for the pricing of climate change in loan spreads using borrowers' exposures to natural disasters as part of the identification strategy. A naive approach to capture the

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

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. Loan spreads is the dependent variable in this specification. As shown in the figure, the effect of climate change-related disaster on loans spreads appears to exhibit a small and positive time trend. Compared to the time period of 1996 to 2001, loans issued by firms following a direct disaster hit carry an additional increase in spread by about 20 to 30 basis points from 2006 to 2019. This approach, however, does not allow us to disentangle changes in loan spreads due to the direct effects of the disaster on borrowers' performance from banks' pricing of the change in the frequency and intensity of these disasters due to climate change.

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

To disentangle these two separate effects of natural disasters on loan pricing, we do not draw inferences from firms that are actually 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.

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

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

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

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

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

Another potentially confounding channel, this time from the lender's perspective, is the potential use of internal-funding across branches by banks. Major disasters may drain funds from branches of a bank in an affected location, which may lead the bank to transfer funds from branches in unaffected locations, reducing their funding, and to an increase in the loan spreads charged to unaffected borrowers (Cortés and Strahan, 2017). We therefore include bank × year fixed effects ($\phi_{m,y}$) in our regressions to capture the time-varying nature of these internal funding markets.[11] 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.[12] We cluster the standard errors ϵ two ways. First is by firm, to capture serial correlation of errors within the same borrower over time. Second is by year, to capture arbitrary correlation of errors for loans taken out at the same point of time.

4.2 Climate change and loan pricing

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

[Table 2 here]

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

In column 2, we add loan-level controls for maturity, loan type, and the presence of financial covenants. Our main coefficient estimate remains economically and statistically very similar, at about 18.8. The same is true

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

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

when we replace these loan controls with firm-level control variables that capture time-varying firm-level credit quality in column 3. These controls include profitability, leverage, and credit rating. The estimate for β_1 in this setting is 19.2. Column 4 presents our most complete specification, which includes the full set of fixed effects, bank controls, and loan controls. The coefficient estimate of β_1 in this specification is about 18.8, which is economically material.

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

An important concern is that these estimates just reflect an update of banks' perception of the effect of any type of infrequent disasters on firms' creditworthiness and are not particularly associated with an assessment of the potential impact of climate change on borrowers. As we note in *Hypothesis 2*, if the pricing effects we are capturing in our specifications truly reflect the effect of climate change, the occurrence of *non-climate change-related disasters* should not lead to adjusted prices in at-risk borrowers' loan spreads. To test this, Table 3 repeats the analysis from Table 2, but it replaces our measures of direct and indirect exposure to hurricanes with analogous measures for non-climate change disasters, i.e., earthquakes.[13] One potential concern could be that the small numbers of earthquake strikes in the United States as captured by the disaster frequencies in Table 1 during our sample period make comparisons between U.S. hurricanes and U.S. earthquakes difficult. As described in section 3, we address this concern by constructing firms' exposures to earthquakes by using their location-weighted ground motion assessment, which is based on the USGS's seismic hazard maps. This measure captures each location's ex-ante potential for ground shaking due to earthquakes.

[Table 3 here]

The coefficients of interest in Table 3 are those on the interaction term $Indirect\ earthquake_{i,t} \times recent\ earthquake_t$. In this particular set of tests, *Recent earthquake* takes the value of one if an earthquake materialized in the United States in the previous three months. In column 1, the coefficient estimate is statistically insignificant and actually

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

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.[14]

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

In an additional test, we rule out the possibility that our results are driven by the potential simultaneous occurrence of a climate change disaster and a non-climate change disaster. In Internet Appendix Table IA.2, we simultaneously include measures of both climate change (e.g., hurricanes) and non-climate change disasters (e.g., earthquakes) in our loan spreads specification. As in our main analysis, we find that the effect of climate change disasters on firms with general exposure to these disasters is associated with a statistically and economically large increase in interest rate spreads of about 19 basis points. As in the analysis in Table 3, the coefficient on $Indirect\ earthquake_{i,t} \times Recent\ earthquake_t$ is negative and statistically insignificant throughout all specifications.

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

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

4.3 Cross sectional effects on high-risk borrowers

Increased borrower risk hurts banks mostly through the threat of default. A financially healthy borrower can weather the damage from a climate change disaster with no impact on their ability to repay their debt. In contrast, borrowers who are close to bankruptcy have the highest risk of defaulting on loans as a result of their exposure to a climate change disaster. If banks indeed price the increased risk from climate change disasters, the price reaction should be more pronounced among borrowers who are more at risk of bankruptcy. We empirically test this conjecture in Table 4 using three proxies for borrower risk.

[Table 4 here]

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

One specific way through which natural disasters threaten firms' creditworthiness is through the threat of destroying physical assets, particularly as those can secure loans. In column 2, we estimate the coefficient for the triple interaction term $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t \times Tangibility_{i,t}$, where $Tangibility_{i,t}$ captures borrowers (normalized) tangibility of assets. Consistent with the threat to physical assets amplifying the effect of hurricanes, the coefficient estimate on the triple interaction is 14, which is statistically and economically significant.

In column 3, we measure borrowers' creditworthiness through credit ratings. The indicator *Non–investment grade* takes the value of 1 for firms rated below investment grade (BBB). The coefficient on the interaction term *Indirect Indirect* $hurricane_{i,t} \times Recent\ hurricane_t \times Non\text{–}investment\ grade_{i,t}$ is 46. Again, this result is consistent with banks pricing climate change risk more intensely when the shocks from climate change disasters are more likely to affect borrowers' ability to repay.[15]

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

4.4 The severity of natural disasters

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

We test this conjecture in Table 5. In our main analysis, we consider hurricanes that caused cumulative damage in excess of \$100 million to define our measure of disaster exposure, and compare them to all the other hurricanes used in our sample.[16] Specifically, we focus on the distinction between regular hurricanes and three super storms with particularly wide-ranging damages exceeding \$100 billion: hurricane Katrina, hurricane Maria, and hurricane Harvey. Table 5 presents the results.

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

[16]In Internet Appendix Table IA.3, we calculate our measure of exposure for cutoffs of \$50 million, \$100 million and \$200 million for our pooled sample of climate change related disasters. As in the case of hurricanes alone, larger disasters are associated with stronger increases in credit spreads.

[Table 5 here]

Column 1 shows that large hurricanes are associated with rate increases that are 31 basis points, about twice the effect of normal hurricanes which are associated with rate increases of about 16 basis points, similar to our main results, in column 2. These results stay unchanged when we estimate them jointly in column 3. Both hurricanes Katrina and Harvey were the most devastating hurricanes recorded at their time, meaning they provided particularly stark data points for lenders to update their risk assessments. Consistent with this interpretation, lenders increase spreads for at-risk, but unaffected, borrowers more starkly after those storms.

4.5 Climate change risk in the secondary market

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

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

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

[Table 6 here]

The results in Table 6 confirm our findings from the study of loan spreads at origination. Across the columns, the secondary market loan prices of at-risk, but unaffected borrowers drop by between two and three percent after a hurricane, which is equivalent to an increase in yield. These results show that investors in the secondary market price climate change risk as a result of increasingly severe natural disasters. The economic magnitude of these estimates is significantly larger than the estimates of the primary loan market. A back-of-the-envelope calculation that links changes in yields to changes in prices suggests that an increase in the annual yield of about 18 bps, taken at the median loan maturity of about five years, translates to a naive change in the loan price of about one percentage point. The estimates from the secondary market are about two times as large as those from the primary market. This finding suggests that there is some selection in the primary loan market, since the most severely affected borrowers do not originate new loans shortly after a disaster, either voluntarily or because they are excluded from the market. Consistent with this interpretation, in unreported results, we find a substantial drop in liquidity in the secondary loan market following climate change disasters, with bid–ask spreads widening above their normal level.[17] Jointly, these findings from the secondary loan market not only provide an independent verification of our primary loan market results but also hint at the negative effect of climate change disasters on loan *access*, which goes beyond our main results on loan *pricing*.

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

4.6 Climate change risk and banks' assessment of default probabilities

Another way of assessing whether our results are impacted by sample selection is by analyzing banks' assessments about the creditworthiness of corporate borrowers by using "credit register" information. We use PDs reported by large U.S. banks as part of their regulatory filings for their corporate borrowers. PDs should be reflected in loan spreads, as they capture the banks "through-the-cycle" expectations of a borrower's likelihood of default. The data collected through the FR Y-14Q form allows us to track the PDs assigned by large U.S. lenders to each individual borrower on a quarterly basis. Thus, we can assess if the PDs for the borrowers that are "at-risks" from climate change-related natural disasters experience persistence changes by their lenders.

In Table 7, we present a specification similar to the one used to analyze the secondary loan pricing data, but using the banks' internally generated PDs as the dependent variable. In this specification, we can track the same bank-borrower pairs over time, so there is no issues related to the sample's composition. However, different from the tests using syndicated loan data originations, the sample period is much shorter, end-2014 to end-2019, due to data availability, which limits power. As in the previous estimation, the coefficient of interest is on the interaction term $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$.[18] In addition to the contemporaneous effect, presented in columns 1 and 2, we also assess the persistence after two quarter, which we present in column 3. Columns 2 and 3, in addition to firm and *Bank*$\times$ *Year-Quarter FE* include time-varying firm controls.

[Table 7 here]

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

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

These results provide additional evidence that banks take into account natural disaster risks associated with climate change in their risk management; especially in recent years as attention to this topic has increased.[19]

4.7 Alternative economic explanations

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

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

[Table 8 here]

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

Another potential explanation for our results could be that the increase in spreads for "at-risk" firms reflects disaster spillovers across supply chains (Barrot and Sauvagnat, 2016). Table 9 tests this conjecture using data from Barrot and Sauvagnat (2016) on specific customer-supplier links to quantify the degree to which borrowers

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

are affected by disasters through their supply chains. As before, odd (even) columns present estimates from the fixed effects only (with firm and loan controls) specifications.

[Table 9 here]

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

An additional channel that could explain our results is the seasonality of hurricanes. Since earthquakes do not follow a seasonal pattern, one might think that borrowers that issue a loan during hurricane season face a risk premium since lenders do not know if a hurricane might strike the borrower soon after. To rule out this alternative explanation, in Internet Appendix Table IA.4 we explicitly exclude all loans made during hurricane season, i.e. June through November, each year. We find that our estimated coefficient on $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ is, if anything, amplified by this restriction. The robustness of our results to this test is not surprising, since our definition of *Recent hurricane* as a lagged 3-month window means that many treated loans are actually made *after* the hurricane season is over.[20]

4.8 Additional robustness tests

We perform a series of additional tests starting with alternative data definitions. These robustness checks are reported in section IA.3 of the Internet Appendix.

First, one concern could be that our sample period features no major earthquakes in the U.S., and the relative absence of major shocks may explain our finding in Table 3, rather than the fact that banks do not update their expectations about the frequency and severity of non-climate change related disasters. To rule out this explanation,

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

we conduct a robustness exercise in Internet Appendix Table IA.5 in which we define *recent earthquake abroad* using the 13 largest earthquakes globally since the year 1996. These disasters include some of the most destructive, high-profile events including the 2004 Sumatra earthquake that caused the Boxing Day Tsunamis, the 2011 Tohoku earthquake followed by the nuclear emergency in Fukushima, and the 2010 Haiti earthquake. If our non-results in Table 3 are due to the small size of events in the U.S., these major earthquakes should elicit a strong pricing reaction. However, the results in Internet Appendix Table IA.5 are economically zero and statistically insignificant in all specifications. This result supports our interpretation that the increased spreads following climate change related disasters reflect an update in lenders' expectation on the frequency and severity of disasters due to climate change, whereas non-climate change related disasters do not elicit updating.

One remaining concern could be that earthquakes are rare in the U.S. during our sample, and the rolling ten–year classification for at–risk counties might not truly capture the earthquake exposure. In Internet Appendix Table IA.6, we re-estimate our earthquake test with an infinite window. We find that the double interaction between recent hurricanes and indirect hurricane exposure measured this way is still statistically insignificant as in Table 3.

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

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

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

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

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

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

5 Time-varying attention to climate change and loan pricing

Banks' ability to correctly price climate change risk depends on their ability to observe it, and there is extensive evidence that investor attention is limited and can be focused by major events. *Hypothesis 3* states that the pricing of climate change related risk should be amplified in periods of high attention to climate change. Therefore, we test for time variation in banks' pricing of climate change-induced lending risk. Specifically, we use the Wall Street Journal (WSJ) index introduced in Engle et al. (2021) to measure time varying attention to climate change.[21]

Panel A in Figure 4 displays the evolution of the WSJ index. It shows two specific features. 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 3rd National Climate Assessment in 2014, or the Paris Agreement at the end of 2015. As noted in *Hypothesis 3*, we should expect stronger pricing reactions for at-risk firms in recent years and during these events when climate change is more salient in the news.

[Figure 4 here]

We present results focused on the time-varying nature of climate change pricing in Table 10. These test are similar to those in our main specification, except for the addition of triple interactions including or standard regressors $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ and measures of climate change attention, including the WSJ index.[22] We expect the coefficient estimate on these interaction term to be positive if banks pay more attention to climate change following periods of attention to climate developments and adjust their interest rates more aggressively for borrowers with exposure to climate change disasters.

[Table 10 here]

In column 1 of Table 10, we find that the estimated coefficient on the triple interaction $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t \times WSJ\ index$, where $WSJ\ index$ is the standardized version of the index in Engle et al. (2021),

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

[22]The WSJ index ends in June 2017, which makes the sample slightly smaller than in our main estimations.

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. These results are consistent with *Hypothesis 3*, which posited that banks should price the impact of climate change-related disasters more starkly when attention to climate change is more salient.

As alternative measures of investor attention to climate change, we obtain data on search traffic from Google for the term "climate change". The data span from 2004 to 2019, and in Internet Appendix Table IA.17 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.18. The evolution of these indexes are presented in panels b and c of Figure 4. 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.[23]

Our findings are robust to these alternative measures. We find that pricing effects are particularly pronounced in times of generally high attention to the relation between climate change and hurricanes.

As a final alternative measure of attention, in Internet Appendix Table IA.19, we use the recent publication of IPCC reports as proxies for public attention. These reports are published about once every seven years. Our sample features three reports in 2001, 2007, and 2014. We designate periods of high attention as the two years following each major report and estimate a triple interaction between an indicator for these years and our main

[23] For example, some of the articles included in the index capture the reporting of news related to the documentary "An Inconvenient Truth".

specification.[24] We find that loan spreads spike substantially more after a hurricane during those years of high attention, with the coefficient estimate on the triple interaction ranging from 87 to 96 basis points.

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

[Table 11 here]

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

This raises the question whether the increased loan spreads that we observe reflect overreaction driven by salience, or whether the transitory price reaction we observe in both primary and secondary markets reflects a correct initial assessment of increased risk, with a subsequent fading due to short memory. In our next test, we investigate this question by testing if the direct damages from hurricanes increase for firms after an indirect hit. If indirect hits act as "warning shots" which tell lenders about the likely future increase in *direct* hits, then firms with *indirect* disaster hits should subsequently see a rise in *direct* damages from disasters. If indirect hits carry no information about the future frequency and severity of disasters, there should be no subsequent increase in direct disaster exposure.

To test this conjecture, we construct a firm-month panel of all our sample firms. We then run regressions of different measures of direct hurricane damage on *Previous direct hit*, an indicator taking value of one for each

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

firm in each month after their first indirect hit. The results are displayed in Table 12.

[Table 12 here]

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

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

6 Corporate finance effects of climate change risk

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

[Table 13 here]

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

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

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

These results show that the most vulnerable indirectly affected firms reduce their investment and increase their cash reserves, which is consistent with updated expectations regarding the increased frequency and severity of future climate change disasters. Interestingly, these effects are rather large and concentrated among borrowers with the lowest access to capital. This could suggest that climate change exposure impacts not just the pricing of capital, but also its availability.

7 Conclusion

We investigate a potential channel where climate change affects corporations through the link between bank lending and climate-change related natural disasters. To 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. The rates that banks charge these indirectly affected borrowers increase by about 18 basis points, or 11% compared to the unconditional loan spread. These effects are strongest for borrowers who are least able to

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

internalize a potential adverse shock, and they are more pronounced for more severe disasters. Consistent with a time-varying attention to climate change, these effects are concentrated in periods of high public attention to climate change, but short-lived.

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

References

Addoum, J. M., Ng, D. T., Ortiz-Bobea, A., 2020. Temperature shocks and establishment sales. Review of Financial Studies 33, 1331–1366.

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.

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.

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.

Beyhaghi, M., Ehsani, S., 2017. The cross-section of expected returns in the secondary corporate loan market. Review of Asset Pricing Studies 7, 243–277.

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.

de Greiff, K., Delis, M. D., Ongena, S., 2018. Being stranded on the carbon bubble? climate policy risk and the pricing of bank loans. Climate Policy Risk and the Pricing of Bank Loans (May 2018). CEPR Discussion Paper No. DP12928 .

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 .

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., 2018. Climate change and long-run discount rates: Evidence from real estate. Chicago Booth Research Paper .

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

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.

Hansen, G., Auffhammer, M., Solow, A. R., 2014. On the attribution of a single event to climate change. Journal of Climate 27, 8297–8301.

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

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

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

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., 2020. Is the risk of sea level rise capitalized in residential real estate? 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., 2020. Firm-level climate change exposure. European Corporate Governance Institute–Finance Working Paper .

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2021. Pricing climate change exposure. Available at SSRN 3792366 .

Seltzer, L., Starks, L. T., Zhu, Q., 2020. Climate regulatory risks and corporate bonds. Working paper .

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.

Webster, P. J., Holland, G. J., Curry, J. A., Chang, H.-R., 2005. Changes in tropical cyclone number, duration, and intensity in a warming environment. Science 309, 1844–1846.

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 (nca4), volume i .

Figures

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

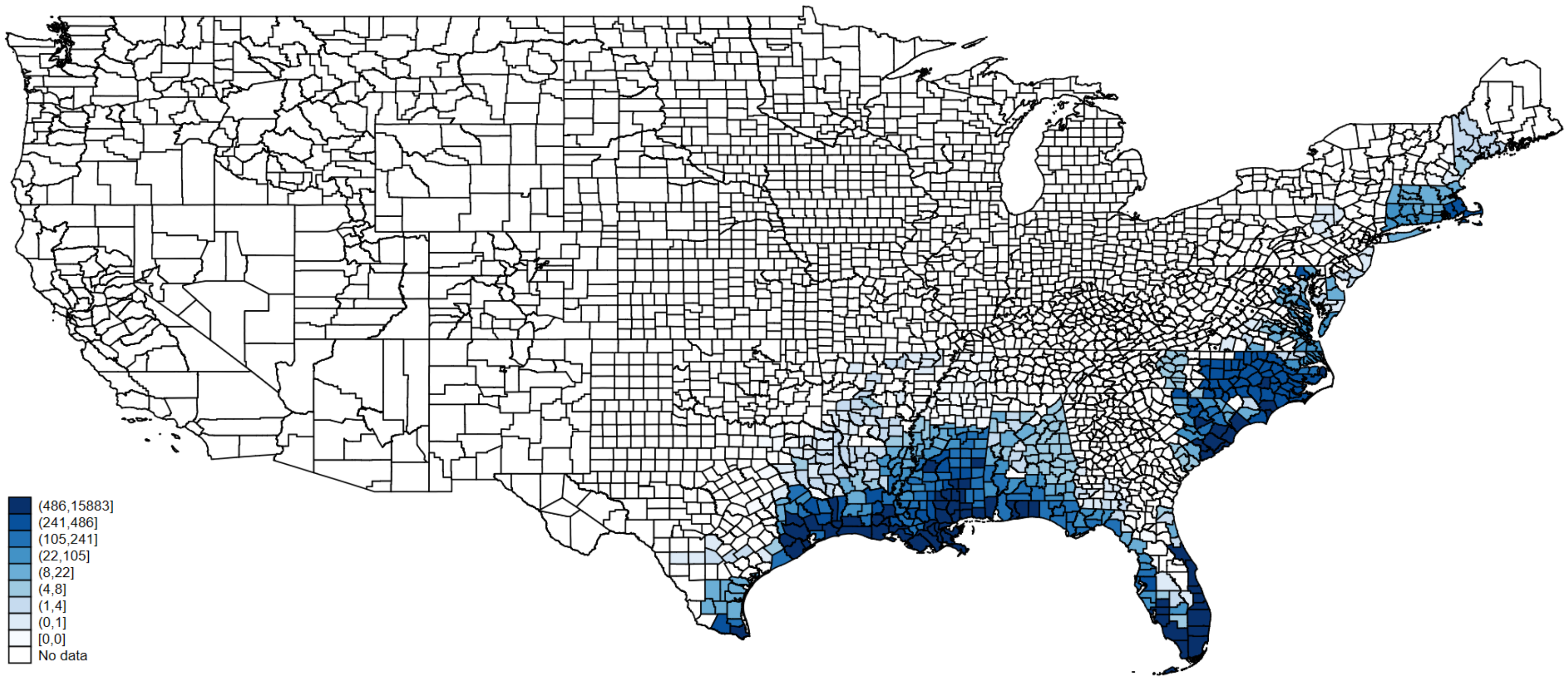


Figure 2: Geographic seismic ground motion assessment 2008
This figure presents county level earthquake exposure in 2008 based on the ground motion assessments of the U.S. Geological Survey (USGS).

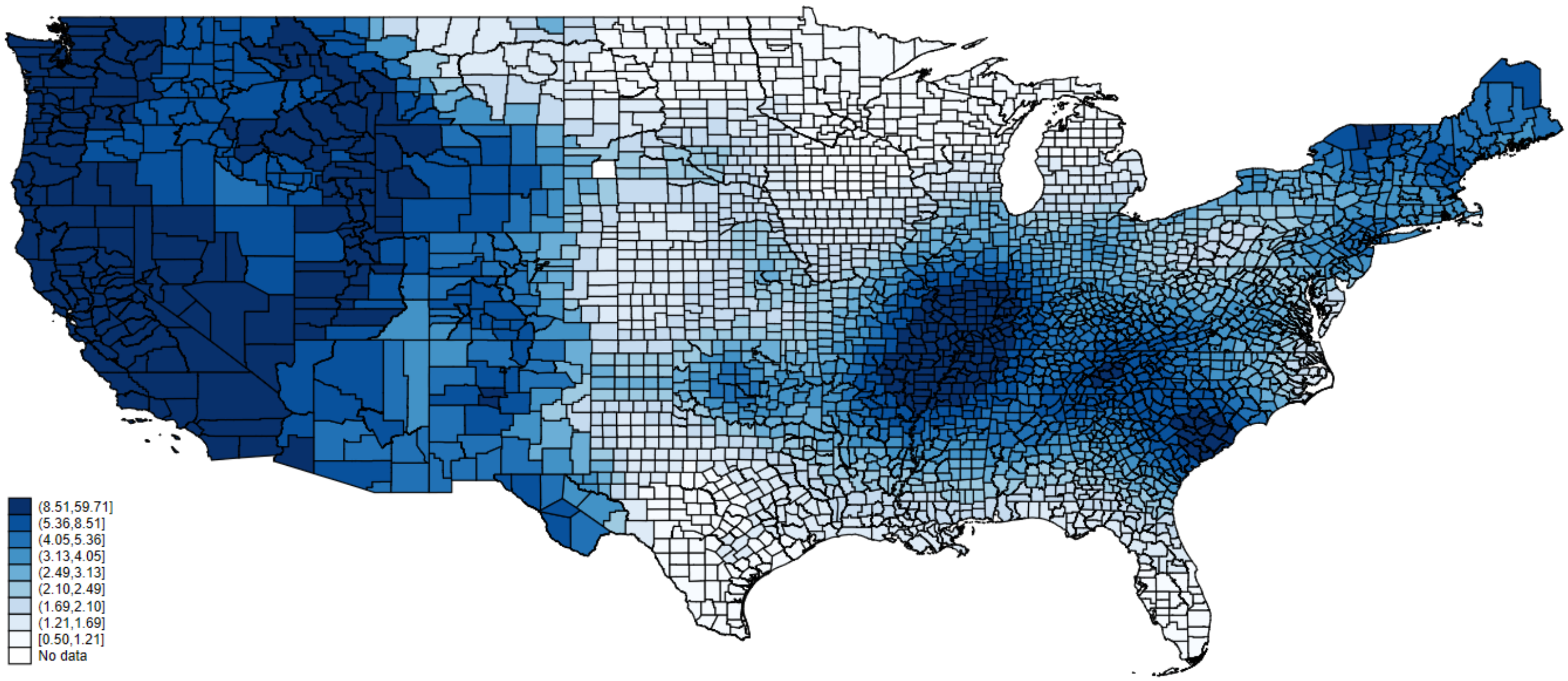


Figure 3: The effect of direct exposure to climate change-related disasters on loan spreads over time

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 2001 form the base period.

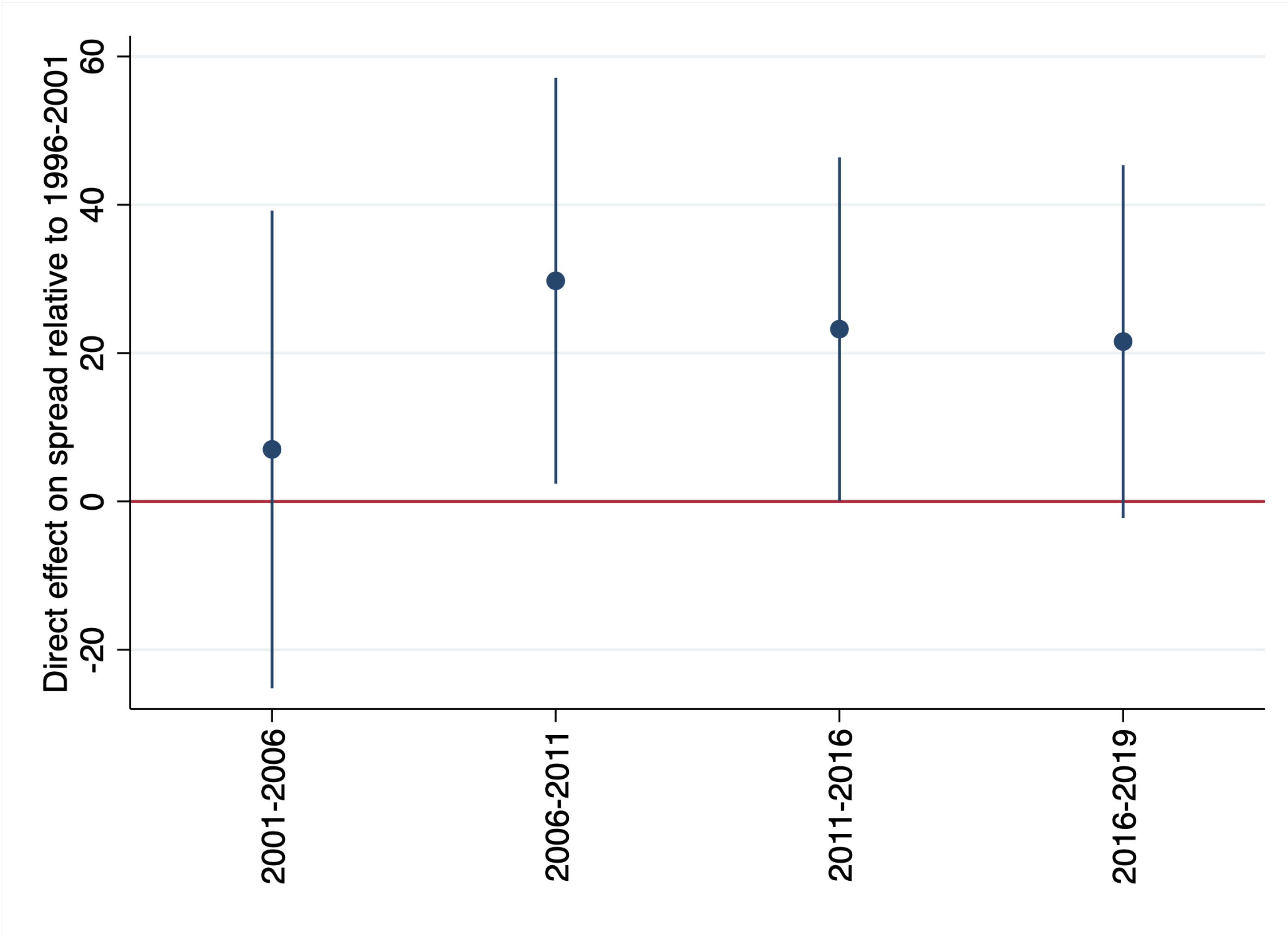
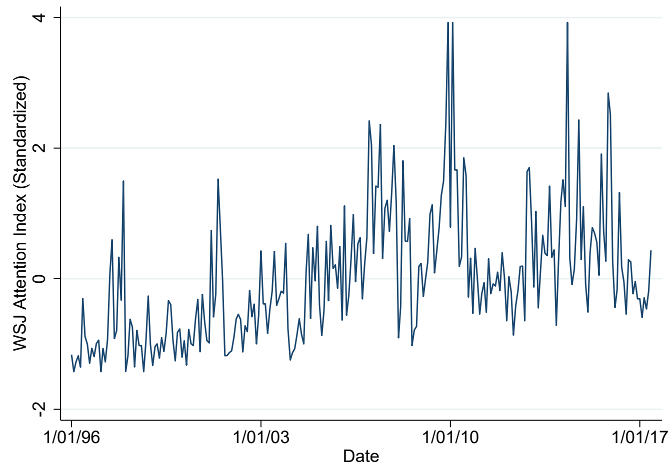
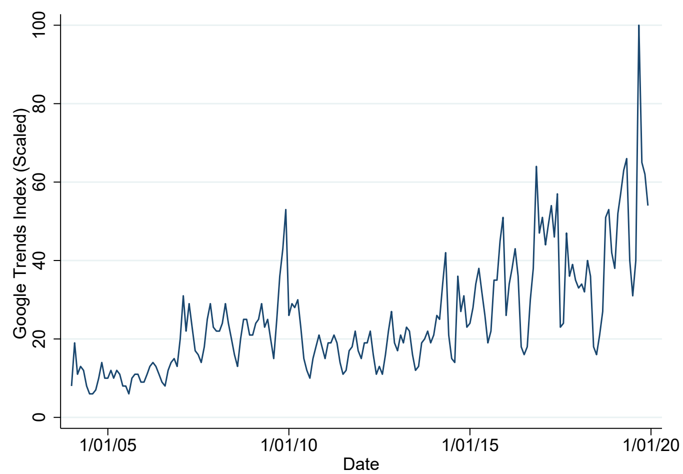


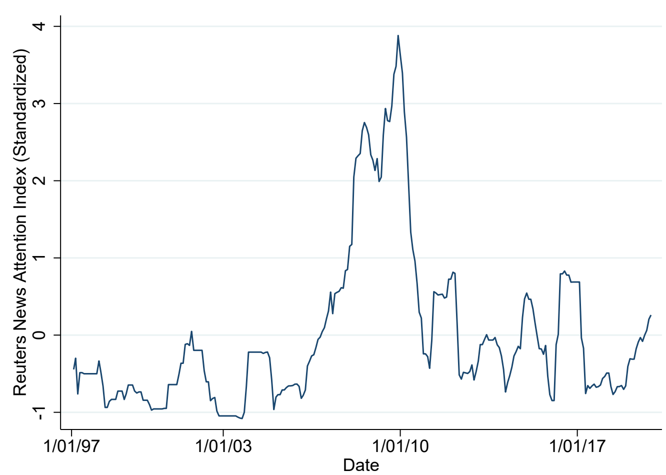
Figure 4: Attention indexes for climate change and natural disasters
This figure presents three different climate change attention indexes. (a) is the standardized Wall Street Journal climate change news index of Engle et al. (2021), from 1996/01 to 2017/06. (b) is the Google search volume of "climate change", scaled by taking the maximus value as 100, from 2004/01 to 2019/12. (c) is a standardized news index based on articles from Reuters News mentioning a connection between storms and climate change as a fraction of all articles mentioning storms during 1997/01 to 2019/12.



(a)



(b)



(c)

Tables

Table 1: Summary statistics

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

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

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

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

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

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

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

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

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

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

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

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

Table 5: Pricing of climate change-related disasters by size of the event
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. *Recent hurricane*$_{>\$100bn}$ indicates the hurricanes with total losses exceeding $100 billion, *Recent hurricane*$_{other}$ indicates the rest of major hurricanes. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 6: Pricing of climate change-related disasters in the secondary market

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

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

Table 7: Banks' internal assessment of climate change

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

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

Table 8: Bank disaster exposures and interest rate spreads

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

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

Table 9: Economic links between borrowers and interest rate spreads

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

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

Table 10: Time-varying attention to climate change
This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding 3 months. *WSJ index* is the standardized attention index constructed in Engle et al. (2021) in the month when a loan is issued, lagged by one quarter. *Above median attention*, *medium tercile attention*, and *top tercile attention* are indicators for loans issued in months with above median, medium tercile, and highest tercile attention to climate change measured by the index, lagged by one quarter. The sample excludes loans to firms that are directly affected by major hurricanes. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 11: Relative time effects

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

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

Table 12: Indirect hits and future severe weather damage

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

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

Table 13: Corporate finance effects of climate change risk

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

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

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

A.1 Variable Definitions

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

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