

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

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Abstract

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Keywords:

JEL Classification: G21, Q51, Q54

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

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November 10, 2025

ABSTRACT

Banks adjust loan spreads after observing natural disasters linked to climate change. We isolate this updating process by identifying loans to borrowers at risk of, but not directly affected by, such disasters. Loan spreads for these borrowers spike in both primary and secondary markets, while no such updating occurs for non-climate-related disasters. Evidence suggests a heightened perceived credit risk, which nonetheless cannot fully explain the increase in rates. Altogether, increased spreads are primarily explained by salience bias, as they are short-lived and amplified by media attention. This salience impacts financial decisions at bank-dependent firms.

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I. Introduction

We investigate whether banks adjust loan spreads in the corporate loan market in response to salient climate-related natural disasters. The potential for increased frequency and severity of extreme weather events due to climate change can have material effects on the economy, including damage to physical assets and disruptions to operations and supply chains (Stern, 2007). With increasing concerns about the potential financial risks associated with climate change, it is important to understand whether banks price this type of risk based on fundamental changes in the creditworthiness of borrowers. If climate change risk is correctly priced, economic activity will adjust or move smoothly away from at-risk geographical areas and economic sectors. However, if banks overreact or otherwise misprice climate change-related risk, the resulting price signals could potentially affect firms that are not experiencing material consequences of climate change and produce inefficient reallocation of resources across geographies or sectors.

Whether and how physical climate-related risk is priced in bank loans is an open question. The majority of physical climate risk is expected to manifest towards the end of the century (Hong, Karolyi, and Scheinkman, 2020). It is unclear whether shorter-lived assets, such as loans, should reflect these risks, as their relevance from today's perspective depends heavily on discount rates (Nordhaus, 2010; Weitzman, 2009), which is why much of the existing literature on climate change and financial markets has concentrated on long-lived assets such as real estate or equities, with an emphasis on estimating discount rates to capture future long-term damages.¹ In contrast, we investigate a novel behavioral channel through which salient climate-related events shape loan pricing today.

According to climate scientists, hurricanes, wildfires, and floods are already intensifying in severity or frequency in North America because of climate change. Banks acknowledge these disasters as climate-related and recognize the risks they impose on loan portfolios.² Since climate change already affects the risks of these disasters today,

¹See, for example, Giglio, Maggiori, and Stroebe (2015); Giglio, Maggiori, Rao, Stroebe, and Weber (2021); Bernstein, Gustafson, and Lewis (2019); Murfin and Spiegel (2020); Baldauf, Garlappi, and Yannelis (2020). One notable exception is Ivanov, Kruttli, and Watugala (2024), who focus on the contemporaneous effects of climate change on bank lending through regulatory responses rather than physical damages.

²We provide extensive anecdotal evidence on banks' statements regarding credit risk from disasters in Internet Appendix section IA.1 and Table IA.1. The United Nations' Intergovernmental Panel on Climate Change (IPCC) provides extensive discussions of these phenomena (e.g., IPCC reports: Field, Barros, Stocker, and Dahe, 2012; Masson-Delmotte, Zhai, Pirani, Connors, Péan, Berger, Caud, Chen, Goldfarb, Gomis, et al., 2021). Recent studies attribute the increased severity of several natural disasters to climate change. The balance of evidence suggests that hurricanes have become more severe in recent years due to climate change, and their

it is likely the first channel to link the physical risks of climate change with borrowers' creditworthiness. We conjecture that if physical climate change risk is priced in loans today, natural disasters are the most plausible avenue.³ We show that loan prices abruptly react to climate-related natural hazards across multiple parts of the loan market, but this reaction is short-lived. Importantly, we document that this pricing is an overreaction to the salience of climate change and is not fundamentally driven by material changes in credit risk.

To identify whether the information contained in climate-related natural disasters is relevant for banks' pricing of corporate loans, we have to develop a strategy that strips out any confounding factors, such as changes in demand for credit due to recovery efforts after disasters. We use an identification strategy that focuses on changes in loan spreads for borrowers with operations in disaster-prone areas, but not directly affected by a specific event. We refer to these as *indirectly affected* or *at-risk, but unaffected* borrowers. Qualitative evidence from bank reports suggests that some of these financial institutions follow a similar strategy to assess the exposure of firms to natural disasters.⁴ This strategy is illustrated in Figure 1. As described in the figure, consider three firms, A, B, and C, where firms A and B are at-risk while C is not. After a hurricane hits firm A, we compare various outcomes between firm B (*at-risk but unaffected*) and firm C (*not at-risk*), effectively examining how the market updates its perception of the creditworthiness of firm B, which avoided the hurricane, after observing the impact of this natural disaster on firm A. This approach separates the immediate impact of disaster strikes from the updated expectations of lenders about the future effects of climate change-related events. Importantly, we use this setup to compare banks' pricing reaction to natural disasters associated with climate change to their reaction to disasters that are not. This provides another layer in our identification strategy. This estimation approach is similar to [Murfin \(2012\)](#), who tracks changes in banks' covenant uses for borrowers after these banks suffer defaults in other, not directly related, parts of their loan portfolio.

To determine firms' exposure to various types of physical climate risk, we utilize detailed geographic exposure

landfalls have caused increasing damage in North America ([Knutson, Camargo, Chan, Emanuel, Ho, Kossin, Mohapatra, Satoh, Sugi, Walsh, and Wu, 2019](#); [Nordhaus, 2010](#); [Risser and Wehner, 2017](#)). Similar patterns have been reported for a range of other types of severe climate change-related weather events ([Stern, 2007](#); [Mendelsohn and Saher, 2011](#)) such as floods ([Van Der Wiel, Kapnick, Van Oldenborgh, Whan, Philip, Vecchi, Singh, Arrighi, and Cullen, 2017](#)) and wildfires ([Abatzoglou and Williams, 2016](#)). By mid-century, extreme weather events could cost 0.5% to 1% of global GDP annually ([Stern, 2007](#)). See Internet Appendix section [IA.2](#) for further details.

³There is evidence that these types of climate risks are already being priced by equity investors, as almost two-thirds of institutional investors surveyed by [Krueger, Sautner, and Starks \(2020\)](#) report that they expect the physical risks of climate change to affect their portfolios today or within two years.

⁴We discuss this evidence in Internet Appendix section [IA.1](#).

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, based on detailed historical disaster hit records, we construct time-varying measures of their exposure to various types of disasters resulting from the geographic footprint of their operations. This operation-weighted disaster exposure allows us to measure borrowers’ general vulnerability to certain types of disasters.

Using these exposure measures and loan spreads at origination from the syndicated loan market from 1996 to 2019, we find that after a hurricane landfall elsewhere, banks charge about 19 basis points higher spreads on loans to *at-risk, but unaffected* borrowers. This increase in loan spreads is economically sizable, representing about 10% of the unconditional spread charged on loans in our sample and is comparable to the impact on spreads of a one-notch rating downgrade. Our results are quantitatively and qualitatively very similar for other disasters associated with climate change such as wildfires and floods.

The increase in spreads for at-risk borrowers following hurricanes, floods and wildfires is specific to climate change-related disasters and not simply a general reaction to tail events. In contrast to these climate-related events, there are no material changes in spreads for placebo tests on natural disasters not associated with climate change, namely earthquakes and winter weather, for a wide range of specifications across both types of disasters.⁵

Moreover, we find that climate-related natural disasters are also associated with price changes in the secondary loan market, with a 2.1% decline in loan prices for *at-risk, but unaffected* borrowers following these events. The implied increase in yields is actually larger than that in the primary market. This is important, as it suggests that selection decisions to borrow in the primary market do not drive our result, and nonbank investors in the secondary market, such as loan funds and collateralized loan obligation (CLO) managers, also react abruptly but fleetingly to these salient climate-related events.

Next, we explore the mechanisms through which climate-related events affect loan spreads. The scientific evidence (Field et al., 2012; Masson-Delmotte et al., 2021) points to an intensification of Atlantic hurricanes, though not necessarily an increase in the frequency of such natural disasters (Dessaint and Matray, 2017).⁶ The change in the observed intensity of climate-related natural disasters could elevate the perceived credit risk of at-

⁵In classifying disasters as climate change related, we follow the IPCC’s long-standing assessments, which find no evidence of increased severe winter weather in North America due to climate change. Instead, these assessments show that warmer winters are related to climate change. We provide a wide range of verification exercises for this classification in the main part of our analysis.

⁶There is similarly mixed evidence for other types of climate-related natural hazards.

risk borrowers. Consistent with a credit risk channel, we find that the pricing effects are amplified for borrowers with higher ex ante vulnerability and we further find some, albeit mixed, evidence for other measures of credit risk, such as external ratings and credit default swaps. Moreover, we find that perceived credit risk, as measured by banks' internal models increases after these events. We observe a significant one percentage point increase in banks' internal model-based assessments of corporate borrowers' probabilities of default (PDs) for indirectly affected borrowers after a hurricane occurrence. However, when we decompose the overall change in spreads for at-risk firms, we find that only a small fraction is explained by changes in fundamental credit risk for these entities, as captured by these measures.

Consistent with the minimal association between default risk and increased spreads, we find that indirect hits generally do not imply that the location of a firm will be hit in the near future.⁷ Overall, our results are consistent with banks and market participants *attempting* to adjust credit spreads to a perceived increase in credit risk, yet over-adjusting in the process.

An alternative to a risk-based explanation for the observed effects on loan spreads (and prices) is hence salience, an overreaction by lenders to the occurrence of disasters. Salience associated with extreme events (Kahneman and Tversky, 1979) can trigger sudden pricing adjustments (Bordalo, Gennaioli, and Shleifer, 2020). One core prediction of salience is that the effects, being driven by recency bias, should be temporary and fade as shocks vanish in the rear view mirror.

We test this prediction by tracing the dynamics of loan spread spikes following indirect hits. We find that the dynamic reaction of loan spreads exhibits a pattern of a sudden spike, followed by a quick reversal for the primary market and for secondary market prices, consistent with salience, while the effect on banks' internal PDs seems to be slightly more persistent. Murfin (2012) finds a similarly steep rise in covenant inclusion following defaults in unrelated borrowers of the same bank elsewhere. Interestingly, like in our case, this sharp rise in covenants is temporary in his setting and largely wanes after one quarter.

To further investigate whether the observed price reactions are due to salience or objective credit risk, we conduct a wide array of tests to assess whether indirect disaster hits carry meaningful information about future direct hits or firm credit risk. We use several approaches to test how much of the pricing changes we capture

⁷While we find generally no increase in disaster incidence or damages, we find a small increase in damages for hurricanes after 2011, but not for floods and wildfires.

are driven by fundamentals compared to behavioral biases (e.g., [Cortés, Duchin, and Sosyura, 2016](#); [Dessaint and Matray, 2017](#)). Based on both climate science and our own tests, which show relatively little predictive power of past indirect hits, our null hypothesis is that banks should not update their risk assessments after observing disasters elsewhere and that spreads should not change significantly after they take place.

Another prediction of salience is that the pricing effect should be amplified by attention. To test this, we construct measures of both time series and cross-sectional attention to climate change. First, we use three measures of time series attention: the Wall Street Journal climate change news index ([Engle, Giglio, Kelly, Lee, and Stroebe, 2020](#)), Google trends data, and a proprietary index we construct from Reuters news articles. We find that the increase in spreads for at-risk borrowers is amplified for climate change-related disasters during times of high attention to climate change. In the cross-section, we find evidence that banks which pay closer attention to climate change-related issues, measured using transcripts of earnings conference calls ([Sautner, van Lent, Vilkov, and Zhang, 2023a](#); [Sautner, Van Lent, Vilkov, and Zhang, 2023b](#)), react more strongly.

While our first contribution is to establish that banks attempt to price climate change risk in corporate loans, the finding that most of this pricing reflects an overreaction is related to the literature on salience in managerial decision making. We explore three distinct dimensions in which the salience to climate change-related disasters exhibited by banks is different from the salience observed in non-financial firms following extreme events.

First, the overreaction in loan prices is topically specific, that is, unique to climate change. We find both no increase in loan spreads for natural disasters that are not associated with climate change, and elevated reactions when attention to climate change is higher both in the time series and cross-section. This result stands in contrast to the literature on salience to general extreme disasters, where non-financial firm executives exhibit salience *even* with respect to disasters unaffected by climate change, like earthquakes ([Dessaint and Matray, 2017](#)). If our results merely reflected banks' salience to rare disasters, rather than a more topical salience associated with climate change, we should see the same spike in spreads for indirectly affected firms following earthquakes or winter weather, which is not what we find.

A second novel finding is that we document salience for a new group of agents. Corporate executives located close to areas affected by natural disasters are shown to make financial decisions that are driven by salience ([Dessaint and Matray, 2017](#)), yet loan spreads are not set by corporate executives. Instead, they are set by

commercial bankers in locations usually different from those of executives borrowing in the syndicated loan market ([Herpfer, 2021](#)). We explore whether the bankers’ and banks’ residence explain the salient reaction to these types of natural disasters. We find that bankers who are more familiar with these natural disasters as a result of their geographical place of residence react less to these types of events by moderating the change in the spreads of the loans they originate. We also find that foreign banks are more prone to adjust the pricing around these natural disasters than US banks. This evidence points to lack of information as one of the drivers of the material reaction to hurricanes. Those who have first-hand knowledge of the impact of these events or that are closer to them tend to overreact less in the pricing of syndicated loans.

Lastly, we examine whether climate change-related salience of lenders is associated with investment decisions of borrowers. Although our results show a transient pricing effect for at-risk firms, this change in spreads represents a material economic cost for firms that raise funds in periods when climate risk is salient. For example, the median at-risk firm experiences an almost \$1 million increase in debt costs if it issues after a hurricane hits elsewhere in the United States, which represent almost a 7% increase relative to its \$14 million, per loan, servicing costs. Consistent with these material economic costs, we find that the most bank-dependent indirectly hit firms, which experience higher spreads and lower loan amounts, reduce their physical capital expenditure by 0.8 percentage points, or about 10% of the unconditional sample mean. At the same time, these firms increase their cash holdings relative to liabilities by about 15% relative to the unconditional sample mean. These findings imply a novel spillover from banks’ overreaction to climate change leading to distortions in firms’ financing and investment choices.

To assess the robustness of our findings, we rule out that various types of spillovers through banking networks (e.g. [Cortés and Strahan, 2017](#); [He, 2019](#)), customer-supplier links (e.g. [Barrot and Sauvagnat, 2016](#); [Pankratz and Schiller, 2024](#)), and regional spillovers through geographic proximity drive the results. Results are similarly not driven by the seasonality of hurricanes and lending, our measures of operational footprints and disaster exposure, or the relative infrequency of U.S. earthquakes. Neither are results driven by firms being directly affected by natural disasters. The staggered aspect of natural disasters also mitigates the concern about potentially omitted concurrent events. Our results are further robust to various measures of attention, placebo exercises regarding the timing of hurricanes, and a wide range of model specifications.

We contribute to the literature on how investors respond to climate change by providing evidence that loan market participants temporarily overreact to salient climate-related disasters, even when borrowers are not directly affected. To the best of our knowledge, ours is the first study to directly link physical climate change risk to corporate loan costs.⁸ The evidence for corporations is largely limited to equity prices. [Engle et al. \(2020\)](#) develop a new measure of climate change risk hedging in portfolios, and [Ramelli, Wagner, Zeckhauser, and Ziegler \(2021\)](#) find that investors reward firms that try to mitigate the effects of climate change. [Krutli, Tran, and Watugala \(2025\)](#) find that option markets price extreme weather shocks. There is evidence that the salient overreaction to disasters by corporate executives spills over firms’ lending terms ([Huang, Jiang, Xuan, and Yuan, 2022](#)) and is also present for mutual fund managers ([Alok, Kumar, and Wermers, 2020](#)) and in options markets ([Ilhan, Sautner, and Vilkov, 2021](#)). A recent literature has found that loan officers are impacted by their personal experiences when setting loan terms ([Dagostino, Gao, and Ma, 2023](#); [Carvalho, Gao, and Ma, 2023](#)). [Delis, De Greiff, and Ongena \(2018\)](#) investigate how banks are exposed to regulations that outlaw fossil fuels, another type of climate risk typically referred to as transition risk ([Financial Stability Board, 2020](#)). Similarly, [Kumar and Purnanandam \(2023\)](#), [Seltzer, Starks, and Zhu \(2022\)](#), and [Ivanov et al. \(2024\)](#) find that firms with higher climate *regulatory* risk face higher debt costs, and future projected sea level rises impact long-term municipal bond yields ([Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2023](#); [Painter, 2020](#)). Our findings highlight the need for robust risk assessment frameworks to account for cognitive biases in order to effectively manage climate-related risks within the financial system.

Another contribution is that we provide estimates on the credit risk banks assign internally to disasters related to climate change. This assessment is crucial, as banks will be prompted to enhance their risk-management related to climate risks if severe weather becomes more intense and frequent. If the increase in loan spreads is transitory and driven largely by salience to climate risks, it may have consequences from a regulatory perspective. Abrupt adjustments in banks’ risk assessments following indirect disaster events may affect firms’ access to financing and increase their cost of funding. Furthermore, our findings imply that the most affected firms internalize the threat

⁸A parallel literature analyzes the effect of natural disasters on banks. [Schüwer, Lambert, and Noth \(2019\)](#) assess the relation between natural disasters and banks’ capital structure, while [Koetter, Noth, and Rehbein \(2020\)](#) and [Cortés and Strahan \(2017\)](#) explore banks’ internal reallocation from unaffected to affected areas after direct natural disaster hits. Although our paper emphasizes corporate loan pricing instead of the volume of lending, we also document a decrease in loan amounts and control for the dynamics observed in those related studies in our pricing tests.

of adverse funding shocks by adjusting their financing and investment activity.

II. Hypothesis development

A possible test to assess whether climate change-related disasters are associated with borrowing costs is to estimate the change in loan spreads as a function of a firm’s direct exposure to those types of disasters. However, this approach faces the challenge that areas prone to these disasters have seen increasing economic activity in recent years, as is the case in Florida for hurricanes and California for wildfires (Nordhaus, 2010). In our analytical framework, we overcome this “Nordhaus-critique” by differentiating two aspects of the impact of disasters on loan spreads: (a) the direct effects (e.g., damages to physical assets, disruptions in the production process, and positive effects due to rebuilding efforts) and (b) lenders’ assessment of the future frequency and severity of these disasters.

To investigate whether banks price the long-running process of climate change, one needs to identify shocks to the underlying assessment of credit risk as a function of beliefs about climate change. We therefore isolate shocks to the expected future severity and frequency of climate change-related disasters by drawing inference from firms that are *at risk* of these disasters, but *not directly affected* at a given point in time. These borrowers are identified based on their operation in at-risk areas from the detailed historical disaster hit records.

A potential confounding issue with this setup is that any change in the loan pricing observed for at-risk firms may simply capture a reaction of banks to any type of rare disaster or tail risk, unrelated to climate change. Therefore, we contrast our main results on climate change-related disasters with placebo tests for non-climate change-related disasters as part of our identification strategy. Using this framework, we test the following hypothesis:

Hypothesis 1:

After a climate change-related disaster, banks charge higher loan spreads for at-risk, but unaffected, borrowers. There is no such effect for disasters unrelated to climate change.

We then proceed to investigate the channel driving the change in spreads. If banks assess a higher probability of default associated with climate change-related natural disasters, they will update their credit risk models to

reflect this information. Moreover, they will adjust spreads more for marginal borrowers, those whose ability to repay would be most severely affected by an adverse shock. To explore banks' internal credit risk assessments, we test the following hypothesis:

Hypothesis 2:

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

Changes in spreads may reflect expectations about adjustments in actual credit risk due to the physical impact of natural disasters and changes due to the salience of these events (Dessaint and Matray, 2017). To distinguish between these two drivers, we need to explore whether the movements in spreads are consistent with the science related to the frequency and intensity of natural disasters, and with measures of actual physical and credit risk. While these explanations are not mutually exclusive, we formally express ways to differentiate between these conjectures as follows:

Hypothesis 3a:

If increases in spreads accurately price changes in physical risks, these changes should be permanent and associated with future increases in disaster exposure and the likelihood of credit events.

Hypothesis 3b:

If pricing changes are the result of salience, they should be temporary and driven by attention to climate-related natural disasters.

We test these hypotheses using detailed measures of exposures to natural disasters, with a distinction on their relation to climate change, which we describe in the next section.

III. Data and sample

To assess the exposures of firms to physical risks, we need to construct a dataset composed of three different layers. The first layer captures the historic exposure of each county to various natural disasters. The second layer captures the geographic footprint of firms, that is, each firm's operations per county. The final layer captures the exposures of banks to these firms. Our analyses use data from a range of sources to construct these three

layers. We combine SHELDUS natural hazard data with firm establishment data from NETS database. We obtain firm data from Compustat, syndicated loan data from Refinitiv’s DealScan, and banks’ risk assessment from the Federal Reserve’s (FR) Y-14Q form. This section describes details of these data sources and sample construction.

A. Data on natural disasters

We obtain data on large natural disasters, which resulted in Presidential Disaster Declarations for Federal Emergency Management Agency (FEMA), from SHELDUS, a county-level natural hazard dataset for the United States from 1960 to the present. The database provides information on the type of hazard, affected location (county and state), year and month, and the direct losses caused by the hazard. These data are widely used in studies on the effect of natural disasters, including studies on bank lending (e.g., [Cortés and Strahan, 2017](#)).

Based on reports produced by the United Nations Intergovernmental Panel on Climate Change (IPCC) (e.g., [Field et al., 2012](#); [Masson-Delmotte et al., 2021](#)), which find substantial evidence of a link between climate change and hurricanes, wildfires, and floods, we classify those disasters as being climate change-related. To support this approach, we provide a wide range of evidence in Internet Appendix section [IA.2](#), from both climate science studies and the perception of market participants, on the link between specific disaster types and climate change. Our baseline specification focuses on hurricanes because they are widely observed, severe, and relatively frequent. We also show that our results hold for climate-related disasters beyond hurricanes. We further contrast our findings with natural disasters unrelated to climate change. While earthquakes are the most clearly unrelated disaster, the IPCC also finds that climate change leads to a reduction in the number of incidents of extremely low temperatures in North America, which are related to *winter weather* in SHELDUS. We, therefore, also conduct tests of winter weather as another type of non-climate change-related disasters.

We focus on the natural disasters with aggregate damages exceeding \$100 million in 2019 constant dollars to make sure that we capture significant disasters. A time indicator, *Recent disaster_t*, flags month t if a certain disaster type hit during the preceding three months. There are five flags as we consider five types of disasters: hurricane, wildfire, flood, earthquake, and winter weather. Since earthquakes are relatively rare in North America during our main sample period, we also construct an alternative measure for recent earthquakes which activates

in the three months following one of the 15 most devastating earthquakes globally during our sample period. Our final natural disaster sample includes 29 hurricanes, 3 earthquakes, 21 wildfires, 37 floods, and 15 winter weather events.

We use SHELATUS to construct each firm’s disaster exposure in multiple steps. First, applying a rolling window approach, we define disaster-prone counties at each time point by assessing historic county-level disaster exposure. For each month and disaster type, we measure each county’s total disaster damage in a backward-looking ten-year window. Figure 2 provides snapshots at the 2019-end of this historical disaster exposure, with graphic representations of each county to the five types of natural disasters mentioned above, respectively. The maps show that our data on disasters reflect the expected geographic distribution. For example, hurricanes cause damages in the southeast and the Atlantic coast, while wildfires are most active along the west coast.

[Figure 2 here]

Applying the monthly historical disaster exposure, we then rank counties and flag with an indicator named *County exposed* $_{c,t}^{disaster\ type}$, those as being *disaster-prone* in a given month for a corresponding disaster type if they are among the top 10% of the distribution. For example, if a county c is a hurricane-prone county in month t , the indicator *County exposed* $_{c,t}^{hurricane}$ will take a value of one, indicating that the total hurricane-related damage county c experienced over the past ten years from month t exceeds that of 90% of counties during the same period. This 10% cutoff corresponds almost exactly with the number of counties that ever have any hurricane exposure. We repeat the same exercise for earthquakes, wildfire, flooding, and winter weather using the same 10% cutoff to define exposed counties for consistency. The benefit of this procedure is that it results in an easily interpretable binary distinction of counties at risk of disasters and those not at risk. In section VII, we show that our results are economically and statistically robust after modifying each of these criteria. Since earthquakes are relatively rare during our main sample period, we again also consider an alternative measure of earthquake exposure, namely time-varying seismic hazard site-specific data from the U.S. Geological Survey (USGS), denoted as *County exposed* $_{c,t}^{seismic}$ for county c in month t which relies on ex-ante potential earthquake risk as opposed to ex post realized risk during our sample.⁹

⁹The 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>. The data project potential peak ground acceleration (PGA) of latitude/longitude

B. Measures of firm exposures to natural disasters

After measuring each county’s time varying exposure to natural disasters, we construct granular corporate geographic footprints to quantify each borrower’s exposure to climate change-related disasters. Deutsche Bank, in a 2018 white paper, captures the intuition of our approach: “Perhaps the most telling metric of a company’s climate risk is the location of its assets and their exposure to changing extreme weather patterns. The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks.”¹⁰ In effect, our measure captures each firm’s physical exposure to climate change through specific natural disasters, as opposed to more global exposure measures such as the ones constructed from earnings calls (Sautner et al., 2023a,b).

We construct detailed geographic footprints of corporate activities using annual snapshots of establishments from the NETS dataset of Walls and Associates. Specifically, each firm i ’s fraction of establishments in a county c in year y is measured as $\frac{Establishment_{i,c,y}}{Total\ establishment_{i,y}}$.¹¹ We then define a company’s exposure to natural disaster risk in each month t as:

$$Firm\ exposure_{i,t}^{disaster\ type} = \sum_c \frac{Establishment_{i,c,y-1}}{Total\ establishment_{i,y-1}} \times County\ exposed_{c,t}^{disaster\ type}, \quad (1)$$

where $County\ exposed_{c,t}^{disaster\ type}$, as defined at the end of section A, is the binary identifier of disaster-exposed counties for each disaster type based on a ten-year rolling window of disaster damage costs. Thus, $Firm\ exposure_{i,t}^{disaster\ type}$ is a location-weighted measure of a company’s exposure to each disaster type. We show in section VII that our results are almost unchanged when allowing for an unlimited time window or various other alternative definitions of $Firm\ exposure$. This measure ranges from 0 to 1, representing each firm’s fraction of establishments in disaster-exposed counties. For example, when focusing on hurricane risk, we apply $County\ exposed_{c,t}^{hurricane}$ to equation (1) and get $Firm\ exposure_{i,t}^{hurricane}$. We follow the same approach for earthquakes, wildfires, flooding,

locations across the conterminous United States since 1996 and allow us to construct a detailed time-varying county-level assessment of exposures to earthquake hazards.

¹⁰A detailed overview of this and similar statements by other lenders is presented in Internet Appendix section IA.1.

¹¹The NETS database contains descriptive information about each establishment starting with its location and parent company, as well as quantitative data such as employment and sales. We only have access to NETS data up to 2014. In our main sample, we carry forward firms’ footprints from 2014 through the end of our sample period in 2019 since these geographic footprints exhibit strong serial correlation. Between loans of the same firm, which are usually spaced apart by about four years, the correlation of hurricane exposure is 0.94. Our results remain economically and statistically unchanged if we stop the sample in 2014.

and winter weather. When applying the USGS seismic assessment as the alternative measure for earthquakes, $County\ exposed_{c,t}^{earthquake}$ in equation (1) is replaced with $County\ exposed_{c,t}^{seismic}$, which gives a firm-level location-weighted earthquake risk measure named $Firm\ exposure_{c,t}^{seismic}$.

Figure 3 presents the cumulative distribution of all six firm disaster exposures across firm-month observations in our main sample.

[Figure 3 here]

As Figure 3 shows, more than 35% of firms have zero hurricane exposure, around 60% have zero earthquake exposure, around 40% have zero wildfire and flooding exposure, and around 35% have zero winter-weather exposure. To make the fraction of treated firms comparable across disasters, we use an indicator $Indirect\ disaster_{i,t}$ to classify a firm as *indirectly exposed*, or “at-risk” to a disaster type, if its operation-weighted exposure is in the top quintile of the cumulative distribution, which results in roughly similar disaster exposure of 10% of operations across disasters. For example, firms indirectly exposed to hurricanes are identified with the indicator $Indirect\ hurricane_{i,t}$. At the top 20% cutoff, $Firm\ exposure_{i,t}^{hurricane}$ is about 0.1, meaning that firms above this cutoff have about 10% of establishments in hurricane-prone counties.¹² In the Internet Appendix, we estimate our main specification with different definitions of this indirect disaster exposure, including variations in the cutoff and directly applying the continuous $Firm\ exposure_{i,t}^{hurricane}$. Our results remain economically and statistically unchanged. More details are reported in section VII.

We also identify firms that are *directly* hit by natural disasters in month t using a similar location-weighted specification: $Direct\ exposure_{i,t}^{disaster\ type} = \sum_c \frac{Establishment_{i,c,y-1}}{Total\ establishment_{i,y-1}} \times Hit\ county_{c,t}^{disaster\ type}$, where $Hit\ county_{c,t}^{disaster\ type}$ is an indicator for counties hit by a certain type of natural disaster in a recent three-month window from month $t - 2$ to t . To avoid our results being contaminated by any potential direct effect of natural disasters, we drop any loans in a firm-month if $Direct\ exposure_{i,t}^{disaster\ type}$ is non-zero for the testing disaster type in all tests. For example, we drop all firms with direct exposure to hurricanes in a test of how spreads adjust following hurricane landfalls. We thus draw inference only from those firms that are *at risk of* a disaster type, but do not experience

¹²The top 20% cutoff value is very similar for wildfire, flooding, and winter weather. The exposure is slightly lower, at about 0.06, for earthquake exposure measured based on historical earthquake records due to the small number of earthquakes in our sample. If measured based on USGS ground motion assessment of PGA, the top 20% cutoff is about 0.1, meaning our indicator for being at risk of a certain disaster consistently flags firms with roughly 10% of their operations in disaster prone locations across the various disaster types.

any direct damages from the specific disaster in a given month. More details can be found in section A.¹³

C. Data on bank loans and risk assessments

In the last step of constructing our dataset, we add syndicated loan data from Refinitiv’s DealScan and balance sheet and income statement data from S&P Compustat. DealScan provides loan information at origination, including loan amount, maturity, and loan spread. We begin our sample in 1996 with the introduction of the SEC’s mandatory electronic filing and include all loans originated in the United States that can be matched with borrowers that appear in the NETS dataset. In total, our sample includes 21,262 loans, issued to 2,522 firms from 1996 to 2019, and is restricted to lead arrangers. We also obtain secondary market loan prices from Refinitiv’s Loan Pricing Corporation from 2000 to 2017. The secondary market data consist of self-reported information from brokers who quote daily prices on loans.

We supplement our data with information on banks’ model-based estimates of PDs for borrowers reported in the Federal Reserve’s (FR) Y-14Q form. This information is collected as part of the Dodd-Frank Act’s stress tests requirements. Bank holding companies with assets above \$50 billion between 2011 and 2018 and above \$100 billion thereafter are required to report such information. The PDs calculated by so-called “advanced approaches” banks are based on banks’ internal risk models as proposed in the Basel II Accord. For banks that are not subject to the advanced approaches regulation, the reported PDs are based on banks’ internal risk ratings. These PDs are one-year “through-the-cycle” default rates, and reflect largely model based risk assessments. For our analysis, we focus on publicly-traded U.S. borrowers that receive commercial and industrial loans. PDs are only available after the end of 2014, which restricts our sample for testing PDs to the period between 2014 and 2019.¹⁴

D. Sample statistics

Table I displays summary statistics of loan characteristics and natural disaster property damages. All variables are calculated as defined in Appendix A.1.

¹³Our results are further robust to various tests that control for spillovers of direct hits, such as removing firms with operations in counties adjacent to directly hit counties.

¹⁴We exclude the oil sector from our sample because oil firms often have hurricane exposure through production assets like offshore platforms or pipelines, which do not qualify as “establishments,” making NETS data inadequate for identifying their exposure. Additionally, the sector experienced significant financial stress during the 2014-2015 oil price drop.

[Table I here]

Panel A covers the 21,262 loans from 1996 to 2019 in our main sample. The median loan is a \$649.73 million (in 2019 U.S. dollars) credit package with a 5-year maturity and a 150.00 basis points credit spread. More than half of the loans have financial covenants, and around three-fourths of the loans are revolving credit facilities. The median borrower in the sample has \$3.60 billion in total assets, with a return on asset (ROA) of 0.12 and a debt-to-asset ratio of 0.33. Panel B shows disaster damage across disaster types. Hurricanes, flooding, and winter weather affect more than 1,900 counties due to their large scale. Though their severity varies by type, all the disasters in our sample are considered severe because they all resulted in Presidential Disaster Declarations for FEMA. At the county level, hurricanes and earthquakes are the most destructive disasters, but all types of disasters show significant damage in the tails of the distribution. Lastly, panel C reports summary statistics for the daily quote price of loans in the secondary market and the PDs reported by banks in their FR Y-14Q filings. The average daily quote and PD are 95.83 and 1.2%, respectively.¹⁵

IV. Climate change and loan pricing

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

A. Empirical setup

As described in section II, our main objective is to test the pricing of physical climate risk in loan spreads using borrowers' exposures to natural disasters as part of the identification strategy.

The main challenge is to disentangle changes in loan spreads due to the direct effects of disasters on borrowers' performance from banks' potential pricing of the change in the frequency and intensity of these disasters due to climate change. Direct exposures to large weather events can have widespread effects on economic and business activity (Dell, Jones, and Olken, 2014), making it difficult to isolate the change in banks' beliefs about climate change from their expectations about potential rebuilding efforts associated with these disasters (Nordhaus, 2010).

¹⁵The period encompassed by the bank internal data is characterized by an economic expansion, which explains the relatively low values for PDs.

For example, damages from hurricanes have increased partly because more people live in hurricane-prone areas that contain more valuable property.

To disentangle these two separate effects of natural disasters on loan pricing, our setup does not draw inferences from firms *directly* hit by these events; instead, we draw inferences from firms that are at risk from climate change-related disasters but that do not experience any direct damages in a given disaster event, corresponding to the indicator variable *Indirect disaster* in section B. Figure 1 presents a stylized illustration of this strategy focused on hurricanes.

[Figure 1 here]

Consider three firms, A, B and C, and assume for illustrative purposes that each operates in a single location. We then track, for each firm and month, whether its location of operations is at-risk of specific natural disasters such as hurricanes. In the example in Figure 1, as shown in Part A, firms A and B are both at-risk of hurricanes, while firm C is not at risk. Then shown in Part B, following a direct hurricane strike on firm A, we compare outcomes (loan spreads, secondary market prices, and PDs) for the at-risk but unaffected firm B, with those same outcomes at the not-at-risk firm, firm C. We refer to Firm B as “indirectly hit” throughout the rest of the paper, while we refer to the case of firm A as a “direct hit”. In effect, we isolate market participants’ updating about climate change risk after they observe a direct hit on Firm A, while carefully excluding the *direct* effects of disaster strikes, overcoming the critique of Nordhaus (2010).

Intuitively, we hypothesize that banks update their assessments of climate change-related disasters partly by observing the effect of these events on corporate 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. However, if the bank updates its prior expectations regarding the severity of hurricanes after observing Harvey, the bank may charge a risk premium for the next loan granted to this hypothetical borrower in Florida. The channel we attempt to isolate is a perceived increase in borrower risk as a result of climate change.¹⁶

¹⁶Recent literature has found mixed results with respect to the effect of disasters on the overall performance of banks (Blickle, Hamerling, and Morgan, 2021; Berger, Curti, Lazaryan, Mihov, and Roman, 2022). Importantly, our setup does not require that banks overall suffer after disasters – it merely requires banks to perceive an increased credit risk for borrowers.

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

$$\begin{aligned} Spread_{i,b,t} = & \beta_1 Indirect\ disaster_{i,t} \times Recent\ disaster_t \\ & + \beta_2 Indirect\ disaster_{i,t} + \beta_3 Recent\ disaster_t + \gamma X_{i,b,t} + \alpha_i + \phi_{b,y} + \epsilon_{i,b,t}. \end{aligned} \quad (2)$$

The outcome variable of interest is the loan spread charged to borrower i by bank b in month t . We drop all loans taken out by borrowers whose operations are directly hit by a natural disaster within three months prior to loan origination; that is to say, the test is only conducted among firms that are not directly hit by a recent natural disaster to avoid contamination of our results. Our main coefficient of interest is β_1 . It measures the effect of $Indirect\ disaster_{i,t} \times Recent\ disaster_t$ on loan spreads, which is the interaction of our time-varying indicator of firms with operations in disaster-prone counties ($Indirect\ disaster_{i,t}$) and an indicator capturing whether a natural disaster has occurred within three months prior to the loan origination ($Recent\ disaster_t$). We expect β_1 to be positive if banks update their prior expectations about the risks of climate change-related disasters after observing the occurrence of this type of disasters.

In estimating equation (2), we control for a number of other factors that may influence loan spreads. 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 $Indirect\ disaster_{i,t}$, which captures that type of risk-taking. Similarly, the indicator $Recent\ disaster_t$ takes the value of one if a natural disaster has occurred in the three months preceding the loan. This variable is not absorbed by year fixed effects and captures the average association between the realization of a disaster and loan spreads. Since most of our sample of firms has geographically far-flung operations, the most severe natural disasters in our sample impact many borrowers, therefore we also include borrower's direct exposure to other types of disasters into the time-varying firm control vector $X_{i,b,t}$, which also includes a wide range of time-varying firm controls (size, profitability, debt-to-asset ratio) and loan controls (loan type, maturity, covenants). Finally, to ensure our estimation is not simply attributable to the spillover effect of the natural disaster on a local economy that spans counties through geographic proximity, customer-supplier links, or common bank networks, we conduct a wide range of robustness checks in section VII.

Besides controls for observable characteristics, we include borrower fixed effects (α_i) to absorb any unobservable

time-invariant characteristics of the firms in our sample. In effect, the fixed effects allow us to compare two loans obtained by the same borrower at two different points in time: one loan obtained during normal times and another loan obtained after a recent natural disaster that indirectly affected the borrower. Importantly, these borrower fixed effects control for a number of alternative, time invariant, explanations, such as the firm’s headquarter location and the industry in which it operates.

Another potentially confounding channel, this time from the lender’s perspective, is the potential use of internal funding across branches by banks. Major disasters may drain funds from branches of a bank in an affected location, which may lead the bank to transfer funds from branches in unaffected locations, reducing their funding, and to an increase in the loan spreads charged to unaffected borrowers (Cortés and Strahan, 2017). We, therefore, include bank $\times$ year fixed effects ($\phi_{b,y}$) in our regressions to capture the time-varying nature of these internal funding markets. Intuitively, this means we are comparing two borrowers from the same bank, in the same year, and the only difference between them is the borrower’s indirect exposure to a recent natural disaster. In further extensions of the model, we include additional quarter fixed effects to account for seasonality in the syndicated loan market (Murfin and Petersen, 2016), and results remain robust when focusing on loans issued during times when seasonal disasters, such as hurricanes, aren’t threatening to hit in the near future (see section VII). We cluster standard errors by firm, to capture serial correlation of errors within the same borrower over time, and by year, to capture the arbitrary correlation of errors for loans taken out at the same point of time.

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

Table II presents the results from estimating various forms of equation (2) focusing on hurricanes. These estimations provide the first test of *Hypothesis 1*.

[Table II here]

The key coefficient in this specification is β_1 , which captures banks’ pricing of climate risks through their assessment of the impact of climate-related natural disasters on loan spreads charged to firms that are indirectly exposed to these events. In column 1 of Table II, the coefficient estimate of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ is 17.3 and is statistically significant at the 5% level. After a climate change-related disaster, banks raise interest rate spreads by about 17 basis points to exposed but only indirectly affected borrowers.

In column 2, we add loan-level controls for maturity, loan type, and the presence of financial covenants. Our main coefficient estimate remains economically and statistically very similar, at 18.8. The same is true when we replace these loan controls with firm-level control variables that capture time-varying firm-level credit quality in column 3. These controls include firm size, profitability, and leverage. The estimate for β_1 in this setting increases to 19.2. Column 4 presents our most complete specification, which includes the full set of fixed effects, firm controls, and loan controls. The coefficient estimate of β_1 in this specification is about 18.8, which is economically material, similar to a one notch credit rating downgrade for investment grade debt. At the median loan amount issued by an at-risk firm, this coefficient corresponds to an increase in funding cost of around \$1 million per loan, or about a 7% increase compared with normal spread costs of \$14 million.

Evidence on the link between climate-related risks and loan pricing is consistent with lenders' stated awareness of the risks that climate change poses to their loan portfolios. In recent regulatory filings, the 10 largest U.S. banks discuss the link between climate change and certain severe weather incidents, and 8 of them mention that climate change potentially intensifies these disasters and poses a material risk to the creditworthiness of borrowers. This anecdotal evidence suggests that lenders, credit rating agencies, and governments have become increasingly aware of the risks of climate change-related disasters for loans.¹⁷

While hurricanes and storms are the most frequently mentioned natural disasters by banks, they also mention two other disasters that, according to the IPCC, are linked to climate change: wildfires and floods. Indeed, when we repeat the tests from Table II for floods in column 2 of Table III (Panel A), we find that spreads increase for at-risk firms by a statistically significant 10.11 basis points, which is equivalent to an increase in loan funding cost of around \$0.5 million for the median at-risk firm after a flood hits elsewhere, or about an almost 9% increase in spread costs. In column 3, we find a similar effect of a roughly 13.02 basis point increase in spreads for at-risk firms following wildfires, equivalent to an increase in loan funding cost of around \$0.6 million for the median at-risk firm after a wildfire hits elsewhere, or an 8% increase in spread costs. Columns 4, 5, and 6 repeat these tests while adding credit rating $\times$ year fixed effects and additional controls at the loan level that are composed

¹⁷As presented in Internet Appendix Table IA.1, some of these banks had already started to note natural disasters as an important risk in 2010. In 2019, all banks in this sample flag those disasters as material issues and link them to climate change. For example, PNC Bank's 2019 10-K filing explicitly states, "Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans." Internet Appendix section IA.1 provides a wide range of examples for this type of awareness on the link between climate change, disasters, and credit risk.

of the loan amount, the loan purpose, and an indicator variable that captures whether the loan is secured by collateral or not. These controls account for time-varying risk premia across the credit risk spectrum. The results remain robust with coefficients of similar or slightly larger magnitude. These results generalize the connection between climate change and spreads we find for hurricanes to other climate change disasters.

[Table III here]

As we note in *Hypothesis 1*, if the pricing effects captured by our specifications truly reflect the impact of climate change, the occurrence of *non-climate change-related disasters* should not lead to adjusted prices in at-risk borrowers' loan spreads. As described in section III, we use the IPCC's assessments to classify earthquakes and winter weather as disasters unrelated to climate change. To test *Hypothesis 1*, Panel B of Table III repeats the analysis from Panel A, but replaces the measures of direct and indirect exposure to climate change-related disasters with analogous measures for earthquakes and winter weather. One potential concern here could be that the small numbers of earthquakes in the United States, as captured by the disaster frequencies during our sample period reported in Table I, makes comparisons between U.S. climate-related disasters and U.S. earthquakes difficult. For instance, measuring firms' exposure to earthquakes based on realized earthquakes could lead to a distorted assessment of at-risk firms. As described in section III, we address this concern by measuring firms' exposures to earthquakes using their location-weighted ground motion assessment, based on USGS's seismic hazard maps. This measure captures each location's ex-ante potential for ground shaking due to earthquakes and avoids the small-sample concern regarding at-risk measurement. In column 1 of Panel B, the coefficient estimate is statistically insignificant and close to zero, in contrast to the positive and significant coefficients for all climate-related perils in Panel A.

In column 2 of Panel B, we repeat this test with the same definition of earthquake exposure as those used for all climate-related disasters, that is, the realized distribution of domestic earthquakes in a rolling ten-year window. The coefficient estimate on the interaction of at-risk firms with recent earthquakes becomes negative and remains statistically insignificant. Another potential concern with this setup could be that the rare occurrence of earthquakes during our sample might induce a statistical power issue even when correctly measuring firms' ex-ante exposure. To alleviate this concern, in column 3, in addition to considering all *domestic* earthquakes per our definition of *Recent earthquake_t*, we construct a list of the most significant earthquakes globally during our

sample periods based on their damages, and continue to find no effect on the spread.¹⁸ Lastly, in column 4 we find a similar null result for the effect of winter-weather events on spreads of indirectly affected firms. Similar to Panel A, columns 5 to 8 of Panel B repeat the same tests with additional controls for time-varying risk premia across the credit risk spectrum, and we still do not find any significant relation between non-climate disasters and loan spreads. While the coefficient estimates in Panel B are somewhat noisy, we note that they are either negative or economically zero. In addition, for all four estimates, the 95% confidence interval excludes our point estimates on the effect of hurricanes of 18.78 basis points.¹⁹

In a parallel set of tests focusing on hurricanes, we examine whether the results on loan spreads extend to other loan terms. Internet Appendix Table IA.2 shows that banks (marginally) lower loan amounts and shorten maturities after indirect hurricane hits. Just like higher spreads, these results are consistent with a perception of elevated credit risk on the part of banks following indirect hits from climate change-related disasters. Taken together, the results in Tables II and III are consistent with hypothesis 1, that banks react to climate-related disasters by increasing the interest rate spread charged to borrowers with significant exposure to these disasters, but not to those borrowers indirectly affected by non-climate disasters.

C. Climate change-related risks and loan pricing in the secondary market

In this section, we investigate whether the occurrence of climate change-related disasters affects loan pricing in the secondary market. Loans in the primary market reflect both the firm’s decision to raise capital and the lender’s assessment of risk at the time of origination. A high loan spread at the time of the initial borrowing could, therefore, be partially explained by selection concerns. On the one hand, at-risk borrowers might avoid raising debt after a disaster, hoping that financing conditions will be more favorable in the future. Then, those who raise capital at that point are the borrowers most desperate for capital, which is why they pay a higher risk premium. On the other hand, it could be that weak, indirectly affected borrowers are shut out of credit markets, and they are unable to raise capital at any price for some time. This would mean that only economically stronger

¹⁸This list is composed of 13 earthquakes including high profile cases such as the 2004 Southeast Asia earthquake that caused an estimated 230,000 fatalities, the 2010 Haiti earthquake with an estimated 250,000 fatalities, and the 2011 Tohoku earthquake followed by the Fukushima nuclear reactor meltdown and more than 10,000 fatalities.

¹⁹In unreported robustness tests, we find that these results are robust if we pool all climate change disasters and non-climate change disasters in two groups, and if we estimate climate and non-climate disaster effects jointly.

borrowers can access capital markets shortly after an indirect disaster strike.²⁰ In this case, higher spreads for newly originated loans in our main analysis would underestimate the true effect of disasters.

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

We report results from this test in Table IV. The outcome variable is the logarithm of each loan’s daily average quote price. Column 1 includes no additional control variables, and column 2 adds loan fixed effects, which capture the average discount at which a loan is trading relative to par. In column 3, we control for year fixed effects to capture time variation in secondary loan prices. Finally, in column 4, our regressions control for both observable and unobservable loan characteristics through loan fixed effects as well as time effects through year fixed effects. To ensure our results are not driven by within-loan time trends in prices, we cluster standard errors at the loan level.

[Table IV here]

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

The economic magnitude of these estimates is significantly larger than the estimates of the primary loan market. A back-of-the-envelope calculation that links changes in yields to changes in prices suggests that an

²⁰Indeed, in an untabulated test, we find that the average firm issuing loans in climate disaster periods is marginally healthier in terms of leverage ratios and asset tangibility.

increase in the annual yield of about 18 bps, taken at the median loan maturity of about five years, translates to a naive change in the loan price of about one percentage point. The estimates from the secondary market are, therefore, about two times as large as those from the primary market. This finding suggests that there is some selection in the primary loan market, with the most severely affected borrowers not originating new loans shortly after a disaster, either voluntarily or because they are excluded from the market. Jointly, these findings from the secondary loan market not only alleviate concerns that selection drives our initial findings, but also show that a group of different investors, such as CLOs and loan funds, changes their behavior similarly to banks issuing loans in the primary market.

V. Credit risk and exposure to climate change-related risks

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

A. Climate change risk and banks’ assessment of default probabilities

In our first set of tests, we analyze banks’ assessments of the creditworthiness of corporate borrowers by using PDs sourced from the U.S. “credit register.” The objective of this exercise is to determine whether the output from banks’ credit risk models is consistent with the higher spreads charged to at-risk borrowers shown in the previous section, which would support the notion that banks are adjusting their models to reflect the potential impact of climate change on the frequency and intensity of some natural disasters. PDs are reported by large U.S. banks as part of their stress test-related regulatory filings. This measure should capture the banks’ “through-the-cycle” expectations of a borrower’s likelihood of default.²¹ The data collected through the FR Y-14Q form allows us to track the PDs assigned by large U.S. lenders to each individual borrower on a quarterly basis. Thus, we can assess if the PDs of at-risk firms experience persistent increases after the advent of climate change-related natural

²¹These PDs are part of the regulatory framework set under Basel II and are typically estimated using internal models managed by large banks, specifically those following the advanced approach (Christensen, 2007).

disasters. These estimates have been shown to be meaningful predictors of actual default (Weitzner and Howes, 2023).

In Table V, we present a specification similar to the one used to analyze the loan origination pricing data, but using banks’ internally generated PDs as the dependent variable. In this specification, we can track the same bank-borrower pairs over time, mitigating concerns related to selection. However, different from the tests using syndicated loan originations, the sample period is much shorter (end-2014 to end-2019) due to data availability, which limits the power of our tests.²²

[Table V here]

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

These results suggest that banks are taking into account some of the natural disaster risks associated with climate change in their risk management, especially in recent years, as some large hurricanes have directly impacted firms in some areas leading to an increase in the likelihood of loan delinquencies.²³ However, changes in the PDs do not fully explain the changes in spreads reported in the previous sections. Setting aside differences in the composition of loans across the two data-sets (both in terms of the cross-section of loans and the time series), and since we find no change in estimated losses given default in unreported tests, a simple back-of-the-envelope

²²As in our main specification, we define a county as at risk of hurricanes if it has suffered any hurricane damage in a ten year rolling window. However, we define hurricane-prone counties as those in the top 30% in each rolling window, as opposed to the top 10% used in the main specifications. Due to the shorter sample period for the PDs dataset compared to our main sample, this procedure slightly expands the number of counties considered as hazard-prone.

²³In unreported results, we find that the likelihood of a firm becoming delinquent on their loans after a direct hurricane hit increased significantly in the 2016 and 2017 hurricane seasons. Those years featured hurricanes that produced large losses, including Harvey, Irma, Maria, and Matthew, which may have influenced banks’ credit risk models.

calculation yields that changes in PDs explain only about one-fifth of the changes in spreads.²⁴

B. Cross sectional effects on high-credit-risk borrowers

We further check the credit risk effect of climate-related disasters by assessing the pricing of loans across firms with different levels of creditworthiness. A financially healthy borrower can weather the damage from a climate change-related disaster with little impact on its ability to repay its debt. In contrast, borrowers who are close to distress have the highest risk of defaulting on loans as a result of their exposure to this type of disaster. If banks indeed price the increased default risk from climate change disasters, the price reaction should be more pronounced among borrowers who are more at risk of bankruptcy. We empirically test this conjecture by focusing on hurricanes and estimating the most saturated model of Table II, which is column 4, and three proxies for borrower risk.

[Table VI here]

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

One specific way through which natural disasters threaten firms' creditworthiness is through the threat of destroying physical assets, particularly those that can secure loans. In column 2, we estimate the coefficient for the triple interaction term $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t \times Tangibility_{i,t}$, where $Tangibility_{i,t}$

²⁴We use the average loss given default reported in the FR Y-14Q submissions and multiply it by the roughly one percentage point increase in PDs estimated in our specifications. That implies a change in the spread of about four bps, or about one-fifth of the roughly 19 bps that we observe in the data.

captures borrowers' tangibility of assets. For ease of exposition, tangibility is normalized to a mean of zero and standard deviation of one. Consistent with the threat to physical assets amplifying the effect of hurricanes, the coefficient estimate on the triple interaction term is 14.5, which is a statistically and economically significant amplification of the base effect.

In column 3, we measure borrowers' creditworthiness through credit ratings. The indicator *Non-investment grade* takes the value of 1 for firms rated below investment grade (BBB). This column shows a coefficient estimate of 45.98 on the interaction term $Indirect\ Indirect\ hurricane_{i,t} \times Recent\ hurricane_t \times Non-investment\ grade_{i,t}$. Again, this result is consistent with banks pricing climate change risk more intensely when the shocks from climate change disasters are more likely to affect borrowers' ability to repay.²⁵ In addition, firms without investment grade ratings have less access to alternative capital sources such as the bond market, making them particularly bank dependent and hence susceptible to banks' perceived climate change risk.

In sum, the findings in this section provide at best mixed evidence for *Hypothesis 2*. Although there is a link between the increase in spreads and the perceived credit risk of at-risk firms, our estimates on banks' internal credit models cannot account for the majority portion of increased spreads. In the next section, we explore other explanations that may be behind these changes in spreads.

VI. Pricing overreaction to climate change

The results presented in the previous section suggest that at most one-fifth of the increase in syndicated loan spreads for at-risk firms observed after hurricanes can be attributed to credit risks associated with climate change-related natural disasters. This section explores our *Hypotheses 3a and 3b*, which together explore the extent to which the increase in spreads is driven by an overreaction to these events, and the potential mechanisms through which this type of overreaction may take place.

²⁵Note that Compustat stops covering credit ratings after the second quarter of 2018, which limits our sample somewhat towards the end in this test.

A. *Is the effect of climate change-related disasters on spreads persistent?*

A key step to assess the mechanism driving the “excess” increase in spreads for at-risk firms is determining whether the change in spreads for these firms is permanent or transitory. For instance, if the change in spread is permanent, it may reflect some adjustment to a banker’s perspective of the fundamentals of the firm that is not yet reflected in banks own risk models. In contrast, if the effect is transitory, it is likely that our results reflect some overreaction or salience to the risks produced by climate change-related natural disasters.

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

[Figure 4 here]

The effect on banks’ internal credit risk assessments, as shown in Section A, seems to be slightly more persistent. In contrast, Internet Appendix Figure IA.1 shows that the pricing effect in the secondary market is even more transitory than in the primary market. This shorter duration could be primarily attributed to the nature of secondary markets, where price discovery occurs more rapidly due to daily trading activities. This differs from the primary market, where offerings are less frequent, and there is often a time gap between a firm deciding to issue and the actual issuance. These figures are consistent with a view that the increase in spreads for at-risk firms is at least partially driven by an overreaction to climate change, potentially due to salience.

B. *Are indirect disaster hits informative?*

In *Hypothesis 3a*, besides the permanence of effects, a key question for attribution of the pricing effect to salience is whether indirect disaster hits actually carry new information about credit risk. If indirect hits act as warning shots that predict future physical disaster damage and credit events, then adjusting spreads is warranted. If,

however, indirect hits do not predict future damages and credit risk, then the temporary rise in rates is likely due to salience. We investigate this question in a series of tests in this section.

[Table VII here]

Specifically, in Table VII, we estimate regressions of measures of credit risk at the firm level, such as credit ratings, credit downgrades, defaults, and market CDS spreads in the year following an indirect hit. We find no effect on ratings, downgrades, and defaults, but a slight elevation in CDS spreads. These results imply that there is no immediate risk of an increase in realized credit events, but an increase in the market perception of credit risk. A further test in Internet Appendix Table IA.3 also shows that indirect hits have no predictive power for future direct hit at the firm level, either in the full sample or in the post-2011 period.

While these tests suggest little informativeness for actual credit events at the firm level, there could still be underlying information at the county level. We perform a series of tests in the spirit of Dessaint and Matray (2017) in which we investigate whether indirect hits carry information about future direct events for at-risk counties. As in Dessaint and Matray (2017), we estimate these tests both for the full sample and the more recent decade since 2011. In Internet Appendix Table IA.4, we find no evidence of predictability of future hurricane hits measured in various ways based on previous indirect hits in the short term, nor any time frame up to two years after an indirect hit, not even for the set of largest hurricanes (Internet Appendix Table IA.5). This result holds for floods and fires (Internet Appendix Table IA.6).²⁶

Finally, we explore whether loan prices differ in levels between at-risk and not-at-risk firms, and whether any such difference increases over time. Appendix Figure IA.2 shows that loan spreads for at-risk firms are, on average, about 10 basis points higher compared to firms not at risk of disasters. However, there is no increase in this premium over time, neither when considering the entire sample or just quarters that do not follow a recent climate disaster.

Taken together, this extensive series of tests suggests that indirect disaster hits carry at most minimal informational content for predicting future credit events. This is further evidence consistent with our results on the

²⁶While there is no evidence of predictability of indirect hits on the extensive margin, there seems to be a modest amount of predictability on the intensive margin, the amount of damages caused by future direct hits. Internet Appendix Table IA.7 finds some predictability of future property damages for the post 2011 period. While this result is largely driven by increased population and inflation, it survives, somewhat marginally, in attenuated form even after accounting for these factors (column 4). However there is no predictability of future damages for any test for floods (Internet Appendix Table IA.8) or fires (Internet Appendix Table IA.9).

temporary pricing effects being most consistent with salience.

C. Is the pricing overreaction influenced by attention to climate change?

One characteristic of salience bias is its amplification by attention. To test *Hypothesis 3b*, we examine the influence of this behavioral response by exploiting variations in attention to climate change across both the time series and the cross-section. The objective is to assess if the transitory “excess spread” observed for syndicated loans is driven by behavioral biases.

First, we use the Wall Street Journal (WSJ) index introduced in [Engle et al. \(2020\)](#) to measure time-varying attention to climate change. This index measures the frequency in which climate change vocabulary appears in the WSJ. It captures the overall market attention to the topic and spikes during times of particular attention to climate change. Panel A in [Figure 5](#) displays the evolution of the WSJ index, which reveals two specific patterns. First, the index has a positive trend, capturing the increasing attention to climate change over time, as featured in the news. Second, the index peaks during widely covered events, such as the 2009 UN climate conference in Copenhagen, the release of the Third National Climate Assessment in 2014, and the Paris Agreement at the end of 2015. Note that the index ends in June 2017, making the sample slightly smaller than our main estimations.

[Figure 5 here]

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

[Table VIII here]

In column 1 of [Table VIII](#), 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. \(2020\)](#), is indeed positive at 41.7 and statistically significant at the 5% level. Our main coefficient on $Indirect\ hurricane_{i,t} \times$

$Recent\ hurricane_t$ remains statistically and economically very similar to our main specification, at 16.6. This result suggests that banks update their loan spreads more decisively in times of high public attention to climate change. In columns 2 and 3, we split the *WSJ Index* attention measure into medians and terciles, respectively, and find that the pricing reaction increases monotonically in the attention to climate change.

As an additional measure of investor attention to climate change, we obtain data on search traffic from Google for the term “climate change”. The data span 2004 to 2019, and in Internet Appendix Table [IA.10](#) 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.11](#). The evolution of these indices is presented in panels B and C of Figure [5](#).²⁷ Our finding that banks react more strongly as climate is more salient in the news is robust to these alternative measures.

Second, we sharpen our inference by examining cross-sectional differences in banks’ awareness of climate change risk, as opposed to the purely time-varying measures reported above. Applying text-based measures created by [Sautner et al. \(2023a\)](#) which directly capture banks’ discussion of climate change risk or exposure in earnings call meetings, we identify banks that express concerns over climate change. In columns 1 and 2 of Table [IX](#), we find that banks elevate loan spreads substantially more if, in their earning call meetings right after a hurricane hit, they discuss climate change risk or climate change exposure.

[Table [IX](#) here]

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

²⁷The 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.

D. What are the drivers of loan pricing overreaction?

After determining that banks overreact when pricing loans for firms at-risk of climate-related natural disasters, we examine the potential biases triggering that behavior. Salience predicts that bankers should update most strongly after disasters with novel information because of the availability heuristic (Kahneman and Tversky, 1979). In Appendix Table IA.12, we test this conjecture by isolating hurricanes with large degrees of novel information based on three measures related to hurricane severity. We find that pricing effects are indeed amplified for hurricanes that are unusually destructive, unusually large, and those striking novel locations. These results are also consistent with models of salience driven by costly information acquisition (Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023).

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

The first difference is that the salience in our setting is topically unique to climate change. That contrasts with the general salience to large recent disasters, which are more broadly established in Dessaint and Matray (2017). We formalized this feature in the second part of *Hypothesis 1*, which we test in Table III described in section B. In those tests, we find strong support that the overreaction we observe is unique to climate change-related disasters.

Second, the economic agents for whom the hurricane is salient are very different across the two studies. In Dessaint and Matray (2017), the agents in question are executives who make decisions on corporate management. In contrast, the individuals that decide to adjust loan spreads are commercial bankers (e.g. Herpfer, 2021).

With this intuition in mind, we can investigate if learning allows agents to react more correctly to climate events. If bankers learn not to over-react to climate change, experienced bankers should react less to hurricanes. To test this conjecture, we obtain the location of bankers associated with the loans in our sample from the authors of Ceccarelli, Herpfer, and Ongena (2023) and identify bankers with personal experience dealing with hurricanes based on their location.²⁸

²⁸The data do not contain detailed location information for every loan in our sample. We set the disaster exposure of bankers

[Table X here]

In Table X, we estimate this effect using a triple interaction between $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ and two measures of bankers' exposure to direct hurricanes: the cumulative number of hurricanes hits (column 1) and damages (column 2) in the state in which the banker is located. In both tests, we find that our main coefficient on $Indirect\ hurricane \times Recent\ hurricane$ remains positive and statistically significant. Thus, after controlling for “geographic” experience at the banker level, banks still raise interest rates spreads by about 17 basis points to the exposed but unaffected borrowers. However, the coefficient estimates on the triple interaction terms are negative and economically large in both cases, suggesting that personal experience allows bankers to better judge the impact of natural disasters and not overreact to climate-related natural disasters.

The results in column 3 provide further evidence about the importance of individuals, showing that bankers with MBA degrees, which are potentially more well trained to rely on data as opposed to emotions, are substantially less prone to overreact to disasters. Column 4 shows that recent personal experience within one calendar year prior to the loan origination has a similar effect as cumulative experience. Bankers that experienced a hurricane in their home state in the last 4 quarters are increasing rates less for indirectly hit borrowers, similar to the finding in Dessaint and Matray (2017) that executives overreact less after repeat exposure. Finally, Column 5 shows that the overreaction effect is substantially amplified for non-U.S. lenders. This is further evidence consistent with a salience channel. While American banks and bankers are used to observing major natural disasters and their impact, foreign lenders have less experience and tend to overreact more strongly.

The finding that recent experience matters prompts the question of the decay of experience. If bankers with recent experience forget about this experience over time, the tempering effect of recent personal experiences could wane with distance to a disaster. In Figure 6, we re-estimate the specification from column 4 of Table X, while gradually increasing the time from personal disaster experience.

[Figure 6 here]

We find that, indeed, the tempering effect of personal disaster experience fades with time. Five years after a personal disaster experience, the coefficient estimate becomes statistically insignificantly different from 0 even at

with undetermined location information to 0. Since the overwhelming majority of bankers are located in New York and Chicago, this imputation should have limited impact on our estimation and, if anything, bias us against finding an effect of bankers' regional exposure on their reaction.

the 10% significance level, and the total magnitude of the coefficient estimate 10 years after a experience shrinks by about two thirds, from 14 basis points initially to about 5 basis points 10 years later. These tests necessarily rely on relatively few observations in the cross section, cautioning us against over interpreting them, yet taken together these tests show that personal characteristics and experience can shield bankers from overreacting to salient events, an interpretation that is consistent with [Álvarez-Román, Mayordomo, Vergara-Alert, and Vives \(2024\)](#), who find that Spanish wildfires lead to a reduction in credit from banks relying on hard information, while local banks with access to soft information continue to provide credit.

The last difference with [Dessaint and Matray \(2017\)](#) is that treated firms in that study are *headquartered* in areas that *are generally not at risk* of hurricanes: the neighboring but non-affected counties. In contrast, our study’s setup explicitly isolates treated firms as those that *are generally at risk* of hurricanes. This means, by design, most treated firms in [Dessaint and Matray \(2017\)](#) cannot learn anything from a near miss, whereas the treated firms (and their lenders) in our paper potentially can learn from indirect hits. The placebo test in Internet Appendix Table [IA.13](#) illustrates this key difference. We estimate an equation similar to equation [\(2\)](#), but follow [Dessaint and Matray \(2017\)](#) to define treated firms as *Indirect hurricane neighbour*. Unlike the coefficient on $Indirect\ hurricane \times Recent\ hurricane$ in our main tests, the coefficient on $Indirect\ hurricane\ neighbour \times Recent\ hurricane$ is insignificant and much smaller in magnitude.

In sum, our results are consistent with a salient reaction by bankers to natural disasters for firms at risk of these disasters. This further supports our partial rejection of *Hypothesis 3a*, as most of the change in observed spreads for at-risk firms are not driven by credit risk. However, consistent with *Hypothesis 1*, the behavioral biases we capture are unique to climate change-related natural disasters, which contrasts with the broad association of firm salience to tail events found in [Dessaint and Matray \(2017\)](#). Banker salience seems to be broader in the geographical context, as it not only impacts bankers that are geographically exposed to those disasters, but also bankers that are located in other areas.

VII. Additional robustness tests

While we exclude firms with any direct disaster exposure from our tests, a remaining question regarding our setup is the possibility of regional disaster spillovers. To assess whether such spillovers are driving our results, we

conduct a set of tests in Table [XI](#).

[Table [XI](#) here]

In column 1, we add another interaction between recent hurricanes and firm operations in counties adjacent to directly hit areas. The resulting measure, *Operations neighbour counties*, controls for a firm’s total footprints in those unaffected counties that are neighbors of the *Recent hurricane*. This variable effectively estimates pricing reactions following hurricanes for firms with adjacent operations. We find that our main estimator for indirect hits remains economically and statistically almost unchanged from our main specifications in this test, while the estimated coefficient for neighboring operations is positive but statistically insignificant.

An alternative way to rule out that geographic spillovers drive our main results is displayed in column 2, where we exclude any loans whose borrowers have any establishment within 100 miles to the *Recent hurricane* affected counties. We again find that the coefficient estimate of *Indirect hurricane* $\times$ *Recent hurricane* remains close to our main specification, indicating that our main finding is not driven by geographic proximity with disaster locations.²⁹

In column 3, we conduct a placebo exercise. We estimate an equation similar to equation (2) but define treated firms as *Indirect hurricane neighbour*, which follows [Dessaint and Matray \(2017\)](#) to use hurricane-unaffected but neighboring counties. Analogous to our main specification, the indicator *Indirect hurricane neighbour* identifies firms in the top quintile of location-weighted exposure in these *neighboring* counties. Unlike the coefficient on *Indirect hurricane* $\times$ *Recent hurricane* in our main tests, the coefficient on *Indirect hurricane neighbour* is economically and statistically effectively insignificant, further supporting the notion that our main findings are not driven by geographic proximity.

The other potential explanation for our results could be that the increase in spreads for “at-risk” firms reflects climate shock spillover across supply chains ([Barrot and Sauvagnat, 2016](#); [Pankratz and Schiller, 2024](#)). Table [XII](#) tests this conjecture using Compustat Segment data on specific customer-supplier links to quantify the degree to which borrowers are affected by disasters through their supply chains ([Cohen and Frazzini, 2008](#); [Cen, Maydew, Zhang, and Zuo, 2017](#)). To measure a firm’s exposure to hurricanes through such economic links, we construct

²⁹We provide results from a range of additional specifications in Internet Appendix Table [IA.14](#) and Internet Appendix Table [IA.15](#). Our main results remain unchanged throughout.

two sets of variables: the first is the fraction of a firm’s customers or suppliers being hit by natural disasters in the last three months (*Customer disaster exposure* or *Supplier disaster exposure*), the second are flags of firms in three terciles (1 is the smallest and 3 is the largest) ranked by non-zero *Customer disaster exposure* or *Supplier disaster exposure*.

[Table [XII](#) 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* $\times$ *Recent hurricane* remains between 18.61 and 19.60 basis points and statistically highly significant. 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.

Another factor that may affect our identification strategy is the presence of business interruption or disaster damage insurance for natural disasters ([Collier, Haughwout, Kunreuther, and Michel-Kerjan, 2020](#)). If a business has insurance contracts for a specific natural disaster, the policy would pay out for damages and business interruptions after a firm experiences a direct disaster hit. The presence of such insurance is yet another reason why studying loan rates after direct disaster hits would provide a biased estimate of the effect of climate change on firms. Importantly, insurance should *not*, all else equal, dampen the adjustment of spreads following an indirect disaster hit. The reason is that as disasters intensify, insurers will raise insurance rates or may even withdraw completely from at-risk markets ([Oh, Sen, and Tenekedjieva, 2022](#)). To the extent that insurance premiums rise, the resulting costs would lower the cash flow of firms and, in the sense of a simple Merton model, increase credit risk, even if these at risk firms were able to obtain insurance.

Finally, we provide a wide range of additional robustness tests in the Internet Appendix. We consider spillovers through bank exposure in Internet Appendix Table [IA.16](#). We also show the robustness of our results with respect to a wide range of sample compositions in Internet Appendix Table [IA.17](#), including potential seasonality in the loan market that could overlap with the seasonality of disasters, and the industry-times-time fixed effect which shows that the pricing effects are not driven by concurrent industry-wide shocks. In another test, we rule out that any potential overlap between direct and indirect disaster hits drives our results in Internet

Appendix Table [IA.18](#). We further provide robustness tests concerning even tighter temporal fixed effects, namely bank by quarter fixed effect in Internet Appendix Tables [IA.19](#) and [IA.20](#). In addition, we test whether the null result on winter weather could be driven by the relatively smaller size of winter disasters compared to climate change disasters by comparing winter weather to similarly-damaging floods and fires in Internet Appendix Table [IA.21](#). In Internet Appendix Table [IA.22](#), we show robustness to various ways of clustering standard errors in panel A and exclusion of hurricanes Katrina and Sandy in Panel B. We estimate version with varying disaster exclusion windows in Internet Appendix Table [IA.23](#). In Internet Appendix Table [IA.24](#), we vary the length of the window through which we define county level disaster exposure. Moreover, we establish robustness with respect to a range of alternative ways of defining disaster exposure in Internet Appendix Table [IA.25](#), and find similar results when measuring geographic footprint jointly considering establishments, employment, and sales in Internet Appendix Table [IA.26](#).

VIII. Effects on corporate policies

In our final set of tests, we investigate whether there are spillovers from banks’ climate change-related adjustment in loan terms to corporate policies. This type of tests allows us to assess whether banks’ overreaction to climate change-related natural disasters has real consequences for firms that are indirectly exposed. We conjecture that such effects would be most plausible for firms that are most dependent on bank financing.

We first identify “bank-dependent” firms by using their lack of an investment-grade credit rating. Earlier results in Table [VI](#) showed that these bank-dependent firms indeed experience the largest increase in financing costs. We then construct an annual panel of corporate investments and cash holdings and estimate a model that links these variables to firms’ indirect exposures to climate-related disasters using indicators similar to those used in our main tests. After saturating the models with firm- and year-fixed effects to draw inferences from changes in corporate decisions within the same firm over time, we present the results in Table [XIII](#). The outcome variables are the ratio of each firm’s investments to its assets, and cash holdings as a fraction of liabilities.

[Table [XIII](#) here]

Consistent with CFOs realizing the risk of potential changes in financing costs and availability, columns 1

and 2 of Table XIII show that, after an indirect hurricane strike and the associated tightening in credit, 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 sizable effect of about 10% compared to the unconditional mean. In columns 3 and 4, we investigate whether lower investment is accompanied by higher precautionary cash holdings. Again, consistent with firms that experience a worsening of credit conditions following an indirect hit becoming more cautious, we find that indirectly affected non-investment grade firms maintain cash reserve buffers about 7% higher after a hurricane than the less vulnerable investment grade firms, an economically large relative increase of 15% relative to the unconditional sample mean.³⁰

We provide additional firm-level evidence on the real consequences of indirect hits. First, estimates from a hazard model suggest that an indirect hit reduces the elasticity of loan-taking with respect to the time since the last loan by 20%.³¹ Conditional on eventually taking out a loan, untabulated results indicate that past indirect hits delay loan issuance by approximately two quarters. These findings support the idea that firms, anticipating temporary overreactions by banks to climate-related events, postpone borrowing until the effect dissipates. Second, as shown in Internet Appendix Table IA.27, historical indirect hits also affect future financing by shifting toward alternative financing sources and shortening bank loan maturity.

Taken together, results above imply a novel spillover from banks’ overreaction to climate change leading to distortions in firms’ financing and investment choices. The most bank-dependent indirectly-hit firms reduce their investments and increase their cash reserves, which is in line with these firms having to face potentially higher funding costs and lower credit access due to banks’ adjustments of loan terms.

IX. Conclusion

We assess how banks’ perception of climate change through observing natural disasters impacts the pricing of loans. We show that market participants in both the primary and secondary market demand increased yields for

³⁰We note that the effects for investment grade borrowers have the opposite sign compared to that for non-investment grade firms. We test for the joint significance of these coefficients and find that the joint effect for investment is statistically different from 0 for non-investment grade firms at the 5% level, while the effect on cash holdings is not jointly statistically significant.

³¹The model is estimated using a Poisson pseudo-maximum likelihood regression with firm-quarter-level controls, as well as firm and time fixed effects. The realization of taking out a loan is positively related to *Time since last loan* (coefficient = 0.0502, $t = 6.85$), but the interaction term *Indirect hit* $\times$ *Time since last loan* is negative (coefficient = -0.01017, $t = 2.04$), indicating a 20% reduction in elasticity (-0.01017/0.0502).

at-risk, but unaffected borrowers following a disaster strike. This reaction is specific to climate change, shared across different types of disasters, and amplified by climate change attention. In contrast, we find no effects across a wide range of markets and specifications for disasters that are unaffected by climate change.

When we turn to the question of whether these effects are priced correctly, we find evidence consistent with the increase in spreads being mostly driven by salience associated with the topic of climate change rather than an accurate reassessment of credit risk. Only a fraction of the change in spreads can be explained by a perceived increase in credit risk, which shows up in banks' internal PD assessments. Across markets and disasters, the spike in spreads is short lived and amplified by attention to climate change in both the time-series and cross-section. We find that salience may be associated with the set of information at the disposal of the banker or bank, including geographical proximity, education, and past experience.

However, banks' overreaction has real effects. Bank dependent firms that experience higher spreads and lower loan amounts following an indirect hit, subsequently reduce investments and increase cash holdings. There is, therefore, a spillover from banks' overreaction to corporate policies.

While we focus on whether physical risk affects borrowing costs for corporations through the link between bank lending and climate change-related natural disasters, many interesting questions remain for future research (e.g., to compare the reaction of banks with that of insurers). The biggest one is whether firms and banks shift their key operations away from regions affected by climate change-related disasters to mitigate the potential medium and long term effects of climate change. We leave this important question for future work.

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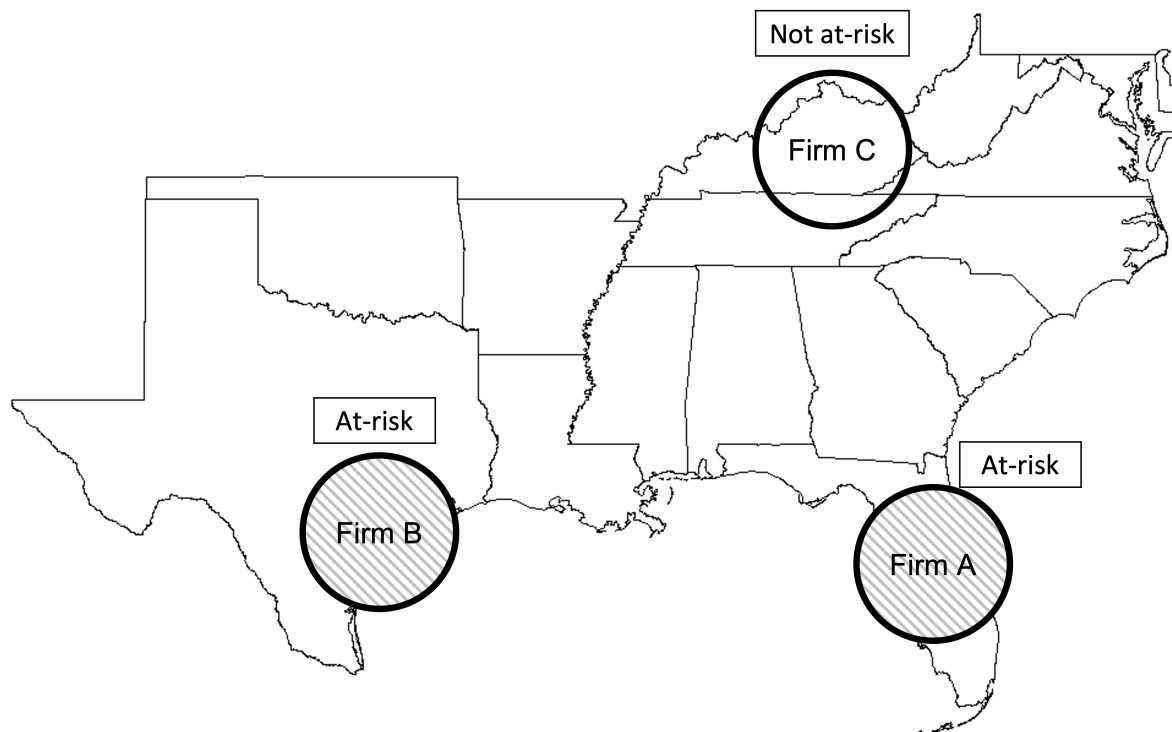
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Figures

Figure 1: Stylized representation of main identification strategy

This figure outlines our main identification strategy. In each month, we dynamically identify the set of firms “at-risk” of each type of natural disaster, e.g. hurricanes, using detailed granular geographic operation footprints. In this illustration, firm A and firm B are at risk (“indirectly affected”), while firm C is not at risk. We then track the occurrence of specific natural disasters and compare loan spreads charged to firms that are at risk, but not directly affected by a specific disaster, such as Firm B, with the spreads charged on loans issued simultaneously to not at-risk firms, such as firm C. We exclude all loans taken out by firms directly affected by disasters such as firm A, from our analysis. In robustness tests we rule out a wide range of potential spillovers from disasters through financial or real channels.

Part A



Part B

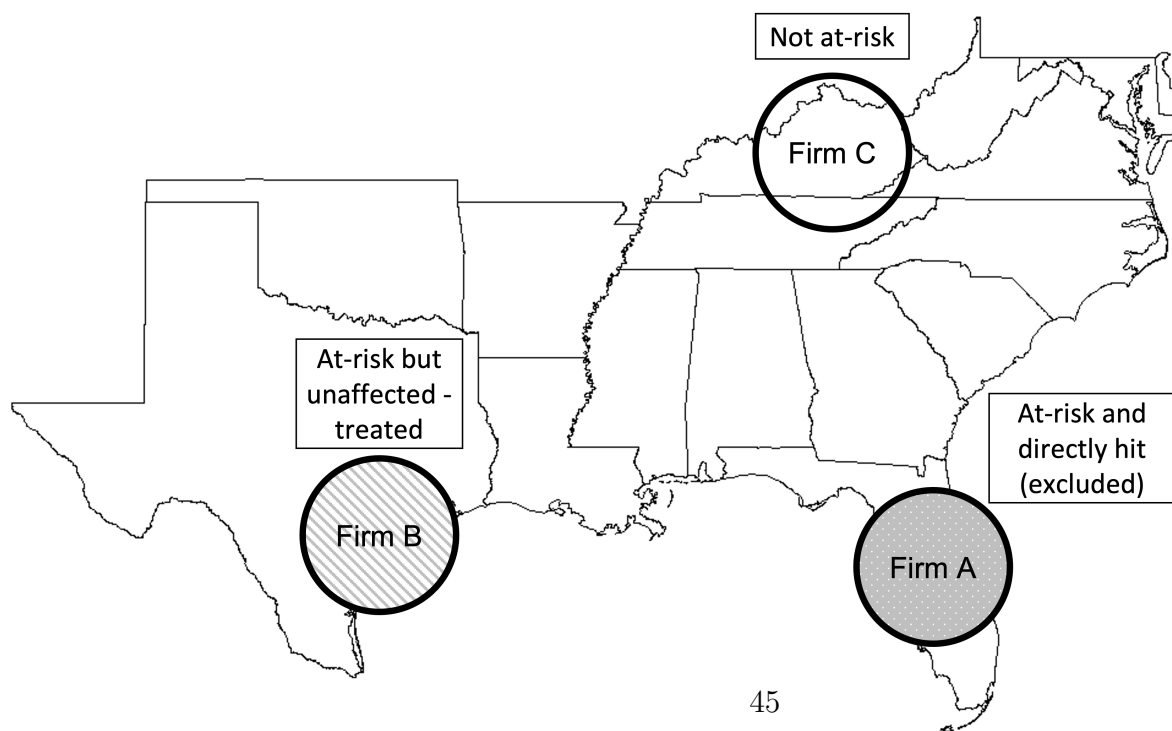
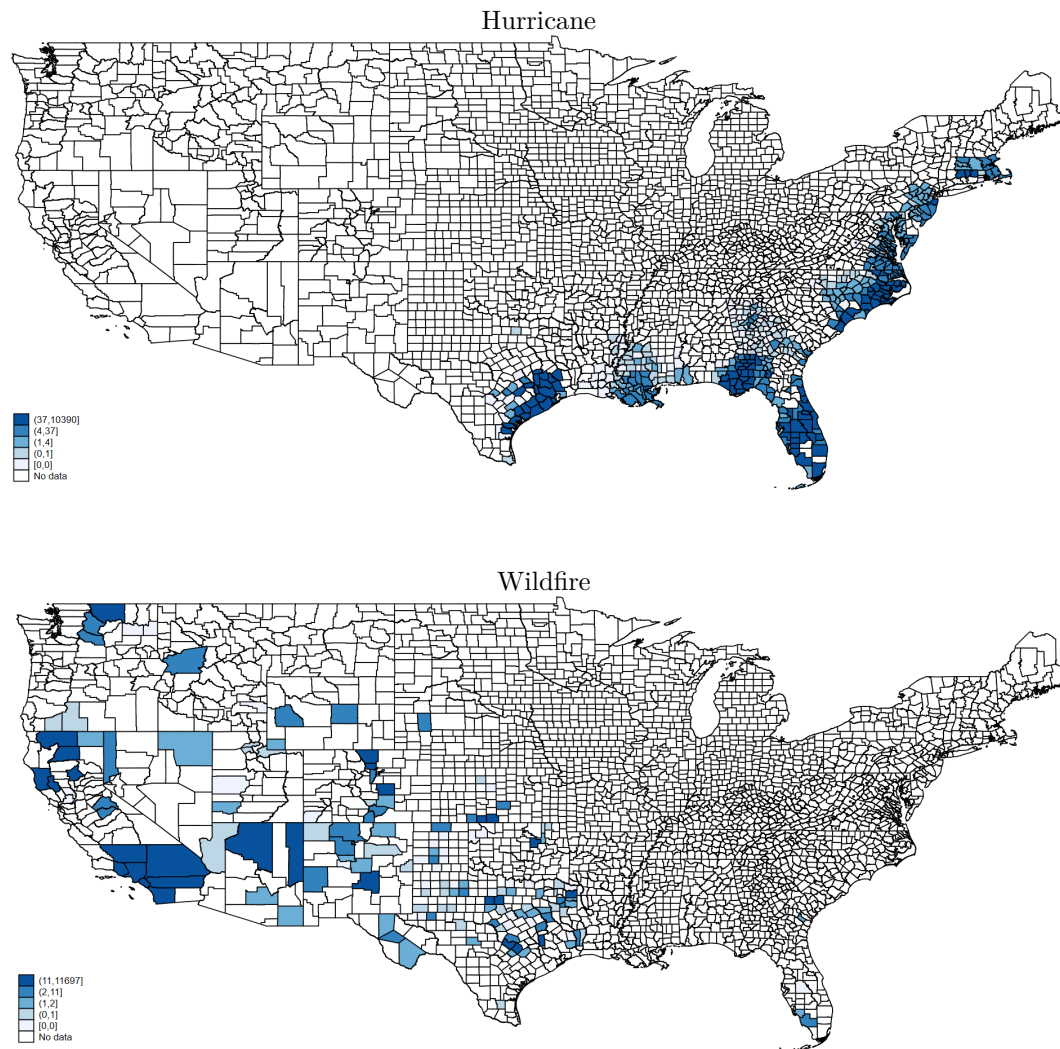


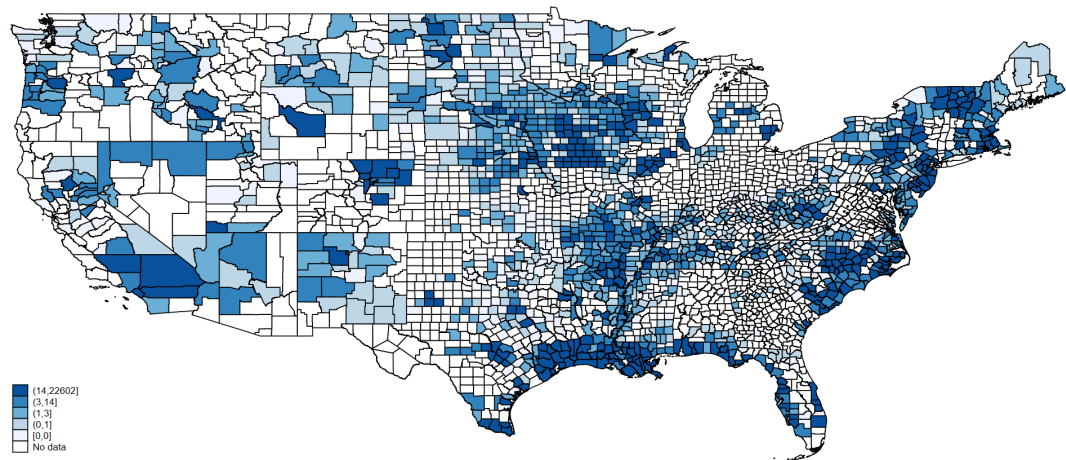
Figure 2: Geographic natural disaster exposure in 2019, based on ten-year disaster records

This figure presents county-level exposure to different natural disasters at the end of 2019. For hurricane, wildfire, flooding, and winter weather, the exposures are based on the total damage (in \$million) caused by the previous ten years' hits from SHELDES. For earthquake, the exposure is based on the latest assessment of peak ground acceleration (in g) by USGS.

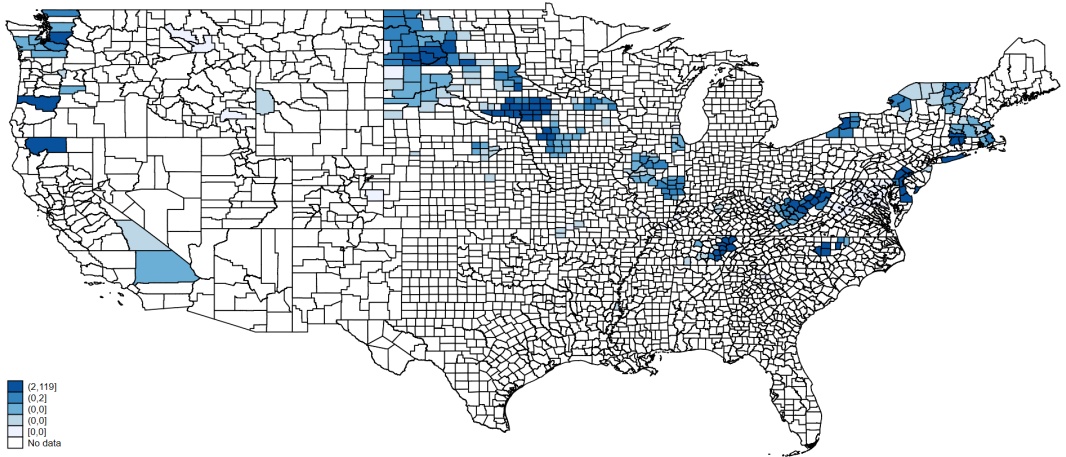


Geographic natural disaster exposure in 2019, based on ten-year disaster records (continued)

Flooding



Winter Weather



USGS Seismic Assessment

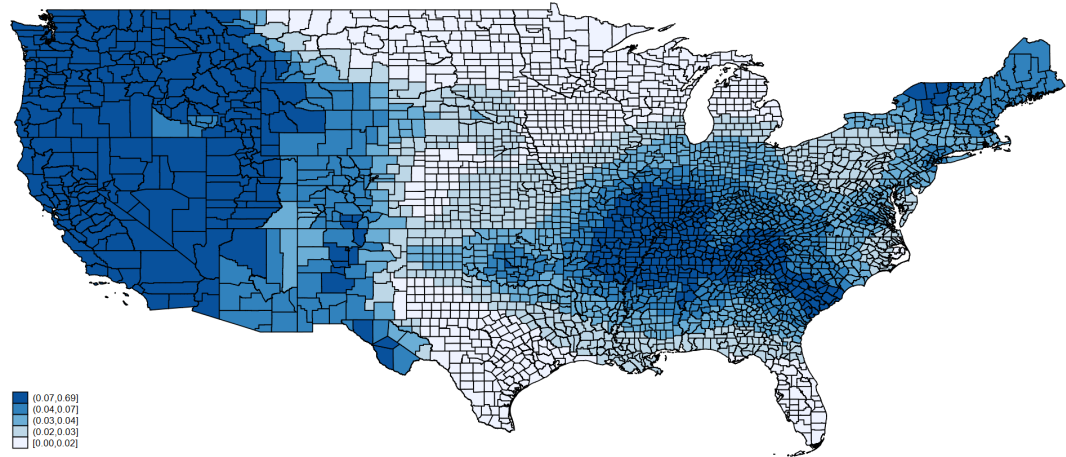


Figure 3: The cumulative distribution of $Firm\ exposure^{disaster\ type}$ for different disaster types

This figure plots the cumulative distribution from 1996 to 2019 of $Firm\ exposure^{disaster\ type}$ for five disaster types: hurricane, earthquake, wildfire, flooding, and winter weather. $Firm\ exposure^{disaster\ type}$ is a firm's monthly location-weighted disaster measure following Equation (1), which represents a firm's fraction of establishments (ranging from zero to one) in disaster-prone counties based on historical records in the first five sub-figures, and represents a firm's average ground motion assessment measured by PGA in the last sub-figure.

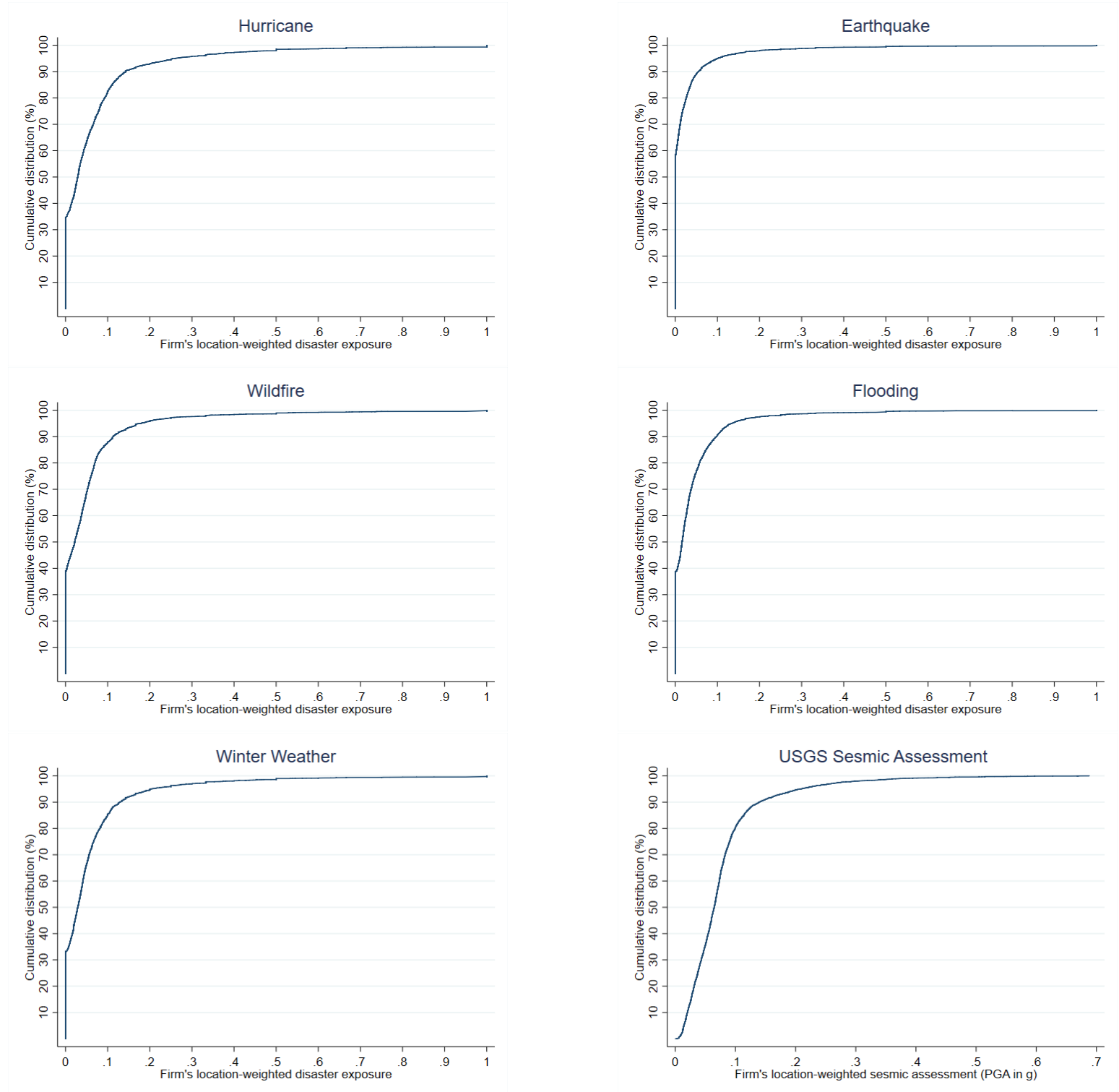


Figure 4: Dynamics of spread reaction in the primary market

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

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

where $Recent\ hurricane_{t-\tau}$ are indicators for occurrences of a hurricane from two quarters prior ($\tau = -2$) to four quarters after ($\tau = 4$) the loan was issued. Other variables are the same with the ones in Table III, including firm fixed effects (α_i), bank $\times$ year fixed effects ($\phi_{b,y}$), credit rating $\times$ year fixed effects ($\delta_{r,y}$), loan-level and time-varying firm-level controls ($X_{i,b,t}$). Vertical lines represent 90% confidence intervals clustered by borrower and year.

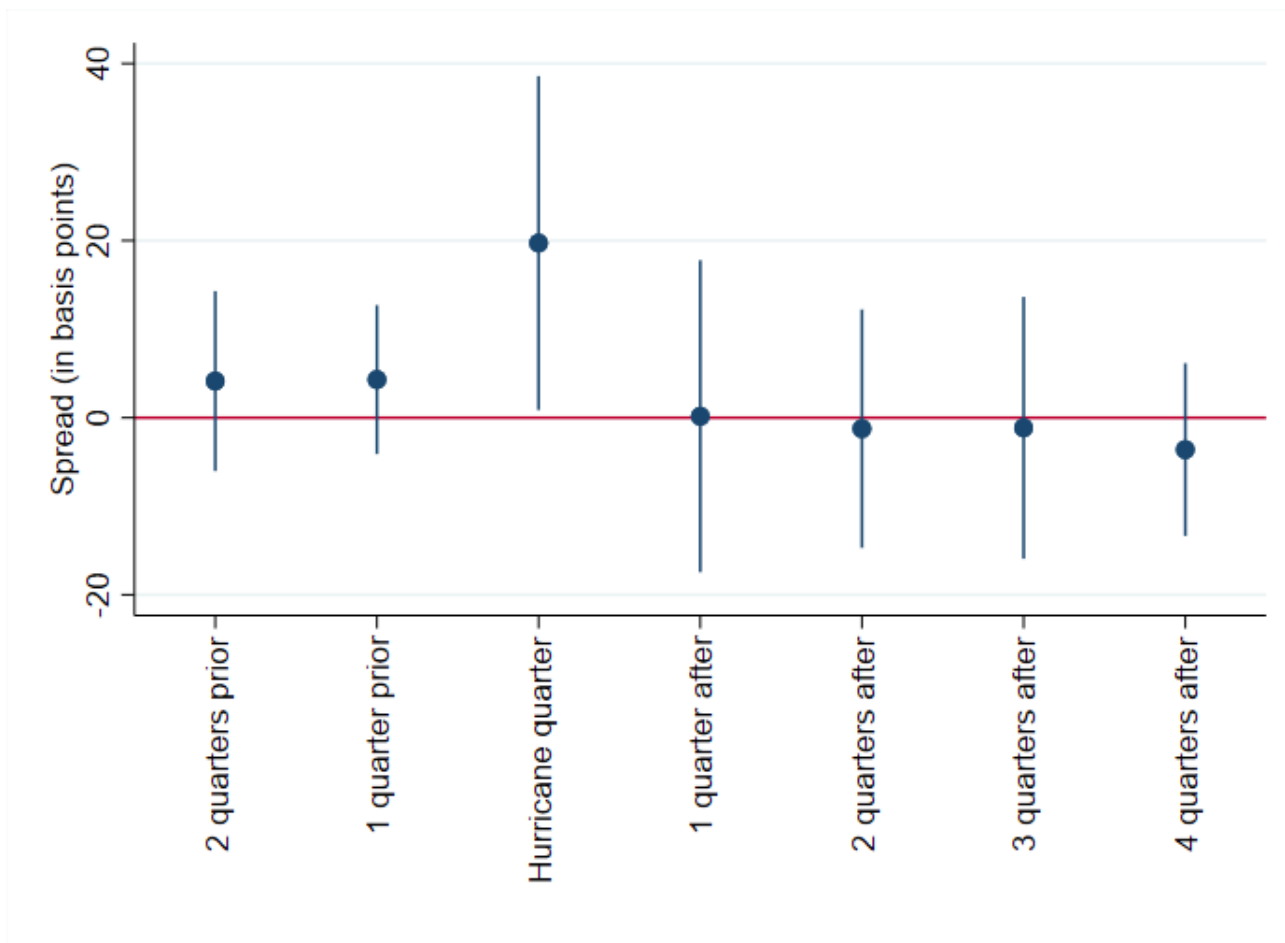
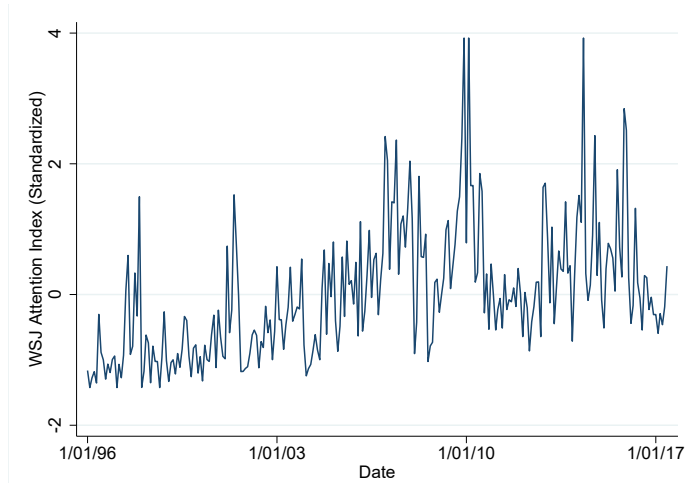
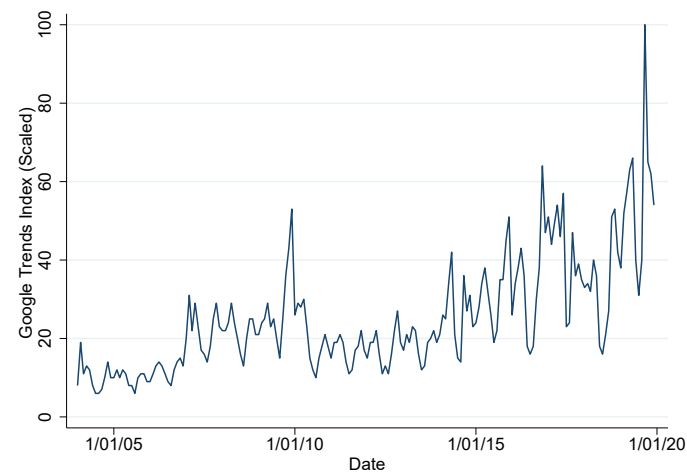


Figure 5: Attention indexes for climate change and natural disasters

This figure presents three different climate change attention indexes. (a) is the standardized Wall Street Journal climate change news index of [Engle et al. \(2020\)](#), from 1996/01 to 2017/06. (b) is the Google search volume of “climate change”, scaled by taking the maximum value as 100, from 2004/01 to 2019/12. (c) is a standardized news index based on the ratio of articles from Reuters News mentioning a connection between storms and climate change among all articles mentioning storms, from 1997/01 to 2019/12.



Panel A: Wall Street Journal climate change news index



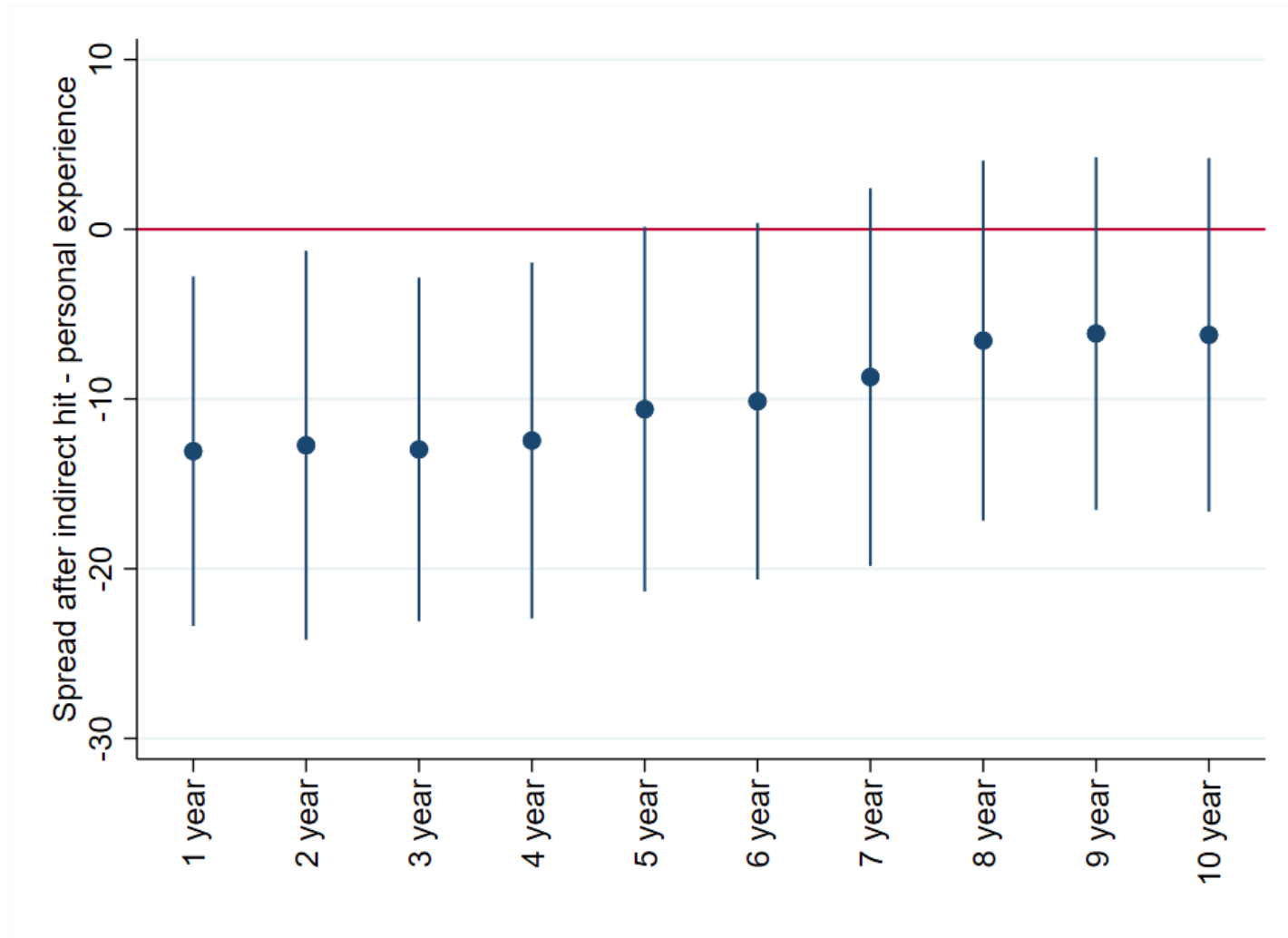
Panel B: Google search trends



Panel C: Reuters News attention index

Figure 6: Effect of banker experience over time

This figure presents the decay of the effect of personal experience of disaster on the banker level over time. Coefficients represent the estimates of the triple interaction term from column 4 of Table X, with the third term being whether a state in which a banker is located has experienced a hurricane in the last year. Each estimate then moves this time window back by one year, up to ten years. Vertical lines represent 90% confidence intervals.



Tables

Table I: Summary statistics

Panel A presents descriptive statistics for loan and borrower characteristics. All variables are explained in Appendix A.1. The sample contains new loan originations matched with lead lenders, and excludes loans to firms directly affected by major hurricanes. All observations are on the loan level. Panel B reports data on property losses from natural disasters. These data are at the county level and cover natural disasters reported in SHELDDUS which the Governor declared a “state of emergency” with a formal request for Federal Emergency Management Agency (FEMA) funds. The sample period of loans and natural disasters is from 1996 to 2019. Panel C reports summary statistics for the daily mid-quote price of loans in the secondary market from 2000 to 2017, and the PDs reported by banks in their FR Y-14Q filings from 2014 to 2019.

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

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

Panel C: The secondary loan market and bank internal data						
	N	Mean	Std Dev	min	p50	max
Daily quote price	62085	95.83	57.53	0.20	98.64	3800
Probability of default	43008	0.01	0.05	0.00	0.0025	1

Table II: Interest rate spreads and climate change-related disasters

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

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

Table III: Interest rate spreads and different types of natural disasters

This table presents results from regressions of loan spread (in basis points) on the interaction of borrowers' indirect disaster exposure indicator with the occurrence of a major disaster in the preceding three months. The type of disasters changes across columns. Panel A reports the results of hurricane, flooding, and wildfire, respectively. Panel B reports the results of earthquakes when *Indirect earthquake* is based on USGS seismic ground motion assessment in columns (1) and (5), when *Indirect earthquake* is based on realized earthquake hits in columns (2) and (6), and when *Recent earthquake* considers the most destructive foreign earthquakes in columns (3) and (7). In columns (4) and (8), we define non-climate change related disasters as winter weather. The sample excludes loans to firms that are directly affected by the major disaster. Loan-level controls include loan maturity, loan type, and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year are reported in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent level, respectively.

Panel A: Climate change-related natural disasters						
	Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
	Hurricane	Flooding	Wildfire	Hurricane	Flooding	Wildfire
<i>Indirect disaster</i>	18.778**	10.105**	13.016*	17.727**	11.203**	16.001**
× <i>Recent disaster</i>	(8.49)	(4.26)	(6.52)	(8.04)	(4.26)	(6.61)
<i>Indirect disaster</i>	3.467	-0.949	-1.559	3.299	-1.669	-2.319
	(3.97)	(4.24)	(3.73)	(3.19)	(4.09)	(3.64)
<i>Recent disaster</i>	1.178	-7.197**	-3.873	2.479	-8.359**	-2.136
	(3.56)	(3.12)	(3.99)	(3.87)	(3.03)	(3.60)
<i>N</i>	21262	19032	21658	21245	19009	21639
<i>R</i> ²	0.742	0.771	0.753	0.775	0.799	0.781
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating × Year FE	No	No	No	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Non-climate change-related natural disasters								
	Spread							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Earthquake	Earthquake	Earthquake	Winter	Earthquake	Earthquake	Earthquake	Winter
	(USGS)	(hit)	(abroad)	weather	(USGS)	(hit)	(abroad)	weather
<i>Indirect disaster</i>	0.495	-5.347	-2.714	1.389	5.057	-15.116	-2.514	-6.053
× <i>Recent disaster</i>	(6.234)	(14.600)	(4.995)	(7.613)	(8.598)	(13.295)	(4.784)	(7.468)
<i>Indirect disaster</i>	-6.187	-0.595	-4.574	-2.624	-3.693	-0.606	-2.06	-0.0586
	(5.634)	(4.308)	(6.052)	(3.470)	(4.124)	(3.657)	(5.258)	(3.233)
<i>Recent disaster</i>	7.795	8.759	0.671	10.118	8.179	10.531	1.993	8.108
	(6.905)	(7.404)	(3.748)	(7.758)	(5.721)	(6.249)	(3.594)	(7.081)
<i>N</i>	23131	24042	23131	23252	23117	24026	23117	23234
<i>R</i> ²	0.734	0.735	0.734	0.736	0.765	0.766	0.765	0.765
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating × Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

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

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

Table V: Banks' internal assessment of climate change

This table reports regressions of banks' assessments of default probabilities on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane. 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, and borrower's direct exposure to non-hurricane disasters, if any. The sum of coefficients captures the sum and significance of the coefficient on the interaction term between the *Indirect hurricane* indicator and the indicator capturing whether there was a recent hurricane. Standard errors double clustered by firm and date are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Probability of default over time		
	(1)	(2)	(3)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane_this quarter</i>	0.011** (0.005)	0.008* (0.004)	0.007 (0.005)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane_1 quarter prior</i>			0.003 (0.005)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane_2 quarters prior</i>			0.003 (0.004)
<i>N</i>	43016	43016	39466
<i>R</i> ²	0.355	0.375	0.374
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Firm controls	No	Yes	Yes
Sum of coefficients			0.012*

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

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

	Spread		
	(1)	(2)	(3)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	17.538* (8.888)	15.877* (8.003)	7.114 (9.292)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Market leverage</i>	25.262* (14.684)		
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Tangibility</i>		14.477* (8.028)	
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Non-investment grade</i>			45.984* (23.960)
<i>N</i>	20269	20616	19658
<i>R</i> ²	0.746	0.741	0.753
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Lower interactions	Yes	Yes	Yes

Table VII: Credit risk and indirect hits

This table reports regressions of various measures of credit risk on exposure to disasters. Dependent variables are on the quarterly level. *Default* is an indicator for firms entering default in a given year. *Downgrade* is an indicator for firms downgraded. *CDS 5y* and *CDS 10y* are the average long term unsecured credit default swap rates for borrowers on 5 and 10 year maturities in a given year, respectively. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and quarter. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Default	Downgrade	Rating	CDS 5y	CDS 10y
	(1)	(2)	(3)	(4)	(5)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	-0.001 (0.004)	-0.003 (0.003)	0.034 (0.128)	0.259** (0.122)	0.222* (0.119)
<i>Indirect hurricane</i>	-0.002 (0.003)	0.002 (0.002)	-0.300 (0.242)	-0.323 (0.214)	-0.284 (0.214)
<i>N</i>	54719	54719	54719	54719	54719
<i>R</i> ²	0.269	0.030	0.785	0.582	0.578
Firm FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Table VIII: Time-varying attention to climate change

This table reports regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. *WSJ index* is the standardized attention index constructed in [Engle et al. \(2020\)](#) in the month when a loan is issued, lagged by one quarter. *Above median attention*, *Medium tercile attention*, and *Top tercile attention* are indicators for loans issued in months with above median, medium tercile, and highest tercile attention to climate change measured by the index, lagged by one quarter. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. The sample excludes loans to firms that are directly affected by major hurricanes. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table IX: Cross-sectional attention to climate change

This table reports regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. *Bank (discuss cc risk)* and *Bank (discuss cc exposure)* indicate, respectively, that a bank discusses climate-change risk or exposure in the earnings call meeting right after the hurricane hit. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Standard errors double clustered by firm and year are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.418 (11.185)	18.816 (11.645)	8.261 (11.484)	10.677 (12.496)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Bank(discuss cc risk)</i>	71.515** (33.066)	65.877* (37.493)		
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Bank(discuss cc exposure)</i>			25.758** (12.683)	21.486* (13.005)
<i>N</i>	12808	12808	12808	12808
<i>R</i> ²	0.682	0.726	0.682	0.726
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	Yes	No	Yes
Lower interactions	Yes	Yes	Yes	Yes

Table X: Salience at the banker level

This table reports regressions of loan spread on the interaction of borrowers' indirect hurricane exposure, an indicator that captures the occurrence of a major hurricane in the preceding three months, and a third interaction term for banker-level variables, standardized for ease of interpretation such that the coefficient estimates can be interpreted as the estimated effect of a one standard deviation in the cross sectional variable. *Cumulative hits* and *cumulative damages* capture the cumulative past exposure of the state in which the banker originating the loan is located to hurricane hits and the associated damages, respectively. *MBA* is an indicator of whether the banker has an MBA. *US parent bank* is an indicator of whether the parent bank is a U.S. bank. We only report the interactions of interest for the sake of readability, all specifications include all lower level interactions. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. Banker data are based on [Herpfer \(2021\)](#) and [Ceccarelli et al. \(2023\)](#). All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread				
	(1)	(2)	(3)	(4)	(5)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.497** (8.537)	16.323* (8.425)	16.931* (8.410)	19.348** (8.381)	46.800*** (13.182)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Cumulative hits</i>	-9.394** (4.503)				
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Cumulative damages</i>		-25.443*** (8.288)			
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>MBA</i>			-24.831** (10.076)		
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Hurricane last year</i>				-13.077** (6.011)	
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>US parent bank</i>					-31.098** (14.037)
<i>N</i>	21262	21262	21262	21262	19495
<i>R</i> ²	0.743	0.742	0.742	0.743	0.733
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes

Table XI: Robustness: geographic proximity with disaster locations

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. The sample excludes loans to firms that are directly affected by the major hurricane. *Operations neighbour counties* is the fraction of a firm's total footprints in the unaffected counties that are neighbours of the *Recent hurricane*. The test in column (2) also excludes loans of borrowers with any establishment located within 100 miles of *Recent hurricane*-affected counties. *Indirect hurricane neighbour* is constructed analogous to *Indirect hurricane* but follows [Dessaint and Matray \(2017\)](#) to use hurricane-unaffected but neighboring counties. 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) Control neighbours	(2) Exclude ≤ 100 miles	(3) Placebo
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.752** (8.487)	21.866** (10.465)	
<i>Indirect hurricane</i>	3.480 (3.975)	3.258 (3.965)	
<i>Operations neighbour counties</i>	8.416 (14.793)		
<i>Indirect hurricane neighbour</i> $\times$ <i>Recent hurricane</i>			4.612 (8.746)
<i>Indirect hurricane neighbour</i>			1.366 (3.850)
<i>Recent hurricane</i>	1.037 (3.685)	-1.922 (4.216)	3.084 (3.817)
<i>N</i>	21262	20616	21262
<i>R</i> ²	0.742	0.747	0.742
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table XII: Robustness: borrowers' economic links 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 last three months. The information of borrowers' supply chain is from the WRDS Analytics Tool using Compustat Segment data based on [Cohen and Frazzini \(2008\)](#) and [Cen et al. \(2017\)](#). *Customer disaster exposure* (or *Supplier disaster exposure*) is the fraction of a borrower's customers (or suppliers) being hit by natural disasters in the last three months. *Tercile1* to *Tercile3* are flags of borrowers in three groups (1 is the smallest and 3 is the largest), ranked by non-zero *Customer disaster exposure* (or *Supplier disaster exposure*), with the base category being zero *Customer disaster exposure* (or *Supplier disaster exposure*). The sample excludes loans to the firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters if any. Standard errors double clustered by firm and year reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.987** (8.610)	19.108** (8.537)	18.610** (8.566)	19.250** (8.551)	18.829** (8.694)	19.603** (8.600)
<i>Indirect hurricane</i>	3.357 (3.969)	3.450 (3.990)	3.190 (3.958)	3.222 (3.910)	3.063 (3.956)	3.198 (3.926)
<i>Recent hurricane</i>	0.804 (3.452)	1.208 (3.460)	1.494 (3.629)	1.118 (3.574)	1.103 (3.521)	1.148 (3.482)
<i>Customer disaster exposure</i> (%)	1.116 (0.816)				1.200 (0.826)	
<i>Tercile1</i> _{<i>Customer disaster</i>>0}		-8.907 (6.595)				-8.980 (6.592)
<i>Tercile2</i> _{<i>Customer disaster</i>>0}		-8.193 (6.161)				-8.596 (6.061)
<i>Tercile3</i> _{<i>Customer disaster</i>>0}		2.600 (8.926)				2.699 (9.053)
<i>Supplier disaster exposure</i> (%)			-0.617** (0.261)		-0.638** (0.259)	
<i>Tercile1</i> _{<i>Supplier disaster</i>>0}				-3.103 (6.423)		-2.909 (6.449)
<i>Tercile2</i> _{<i>Supplier disaster</i>>0}				13.744* (7.903)		14.066* (7.892)
<i>Tercile3</i> _{<i>Supplier disaster</i>>0}				-7.065 (8.606)		-7.003 (8.468)
<i>N</i>	21262	21262	21262	21262	21262	21262
<i>R</i> ²	0.742	0.742	0.742	0.742	0.743	0.743
Bank $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table XIII: Corporate finance effects of banks' reaction to climate change

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

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

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

A.1. Variable Definitions

Loan Variables	
Financial covenant	Indicator equal to one if the loan contract includes covenants
Loan amount	Loan amount in dollars, adjusted to 2019 values
Maturity	The number of years between loan start and end dates
Number of financial covenants	The number of covenants in a loan contract
Revolving loan	Indicator equal to one if the loan type is revolver
Spread	The all-in-drawn spread in basis points
Term loan	Indicator equal to one if the loan type is term loan
Disaster Variables	
County exposed $_{c,t}^{disaster\ type}$	Indicator equal to one if county c in month t , during the past 120 months, exceeds 90% of other counties nationwide in terms of disaster damages caused by a certain disaster type, <i>disaster type</i> changes among “hurricane”, “earthquake”, “wildfire”, “flooding”, and “winter weather”.
County exposed $_{c,t}^{seismic}$	The peak ground acceleration (PGA, in the unit of g) of county c in month t . The PGA assessment is conducted by the U.S. Geological Survey (USGS) of the U.S. Department of the Interior.
Establishment $_{i,c,y}$	The number of establishments that firm i has in county c in year y .
Firm exposure $_{i,t}^{disaster\ type}$	The location-weighted exposure of firm i ’s fraction of establishments in disaster-exposed counties in month t , ranging from 0 to 1, defined as $\sum_c \frac{Establishment_{i,c,y-1}}{Total\ establishment_{i,y-1}} \times County\ exposed_{c,t}^{disaster\ type}.$ Disaster type changes among “hurricane”, “earthquake”, “wildfire”, “flooding”, “winter weather”, and “seismic”.

Indirect disaster $_{i,t}$	Indicator equal to one if firm i is in the top quintile in month t ranked by $Firm\ exposure_{i,t}^{disaster\ type}$. Disaster type changes among “hurricane”, “earthquake”, “wildfire”, “flooding”, “winter weather”, and “seismic”.
Recent disaster $_t$	A time indicator equal to one if a certain type of disaster hit during the preceding three months. Disaster types change among “hurricane”, “earthquake”, “wildfire”, “flooding”, “winter weather”, and “foreign earthquake”.
Total establishment $_{i,y}$	The total number of establishments that firm i has in year y .
Other Variables	
Banker direct hurricane	Indicator equal to one if a loan’s banker is located in a state that has a direct hurricane hit in the quarter of the loan origination.
Bank (discuss cc risk)	Indicator equal to one if a bank discusses its climate-change risk in the earnings call meeting right after a hurricane hit.
Bank (discuss cc exposure)	Indicator equal to one if a bank discusses its climate-change exposure in the earnings call meeting right after a hurricane hit.
Banker hurricane severity	The damages (\$ million) caused by hurricanes in the state of the banker in the quarter of the loan origination.
CapEx/Assets	Borrower annual physical capital expenditure (PP&E) over assets.
Cash/Liabilities	Borrower annual cash divided by current liabilities.
Market leverage	The normalized value of firms’ market leverage ratio.
ROA	Borrower return on asset calculated as net profits over total assets.
Tangibility	The normalized value of firms’ tangibility of assets.
Total assets	Borrower total assets in USD billions.
Non-investment grade	Indicator equal to 1 for firms with a senior unsecured credit rating below investment grade (BBB) in S&P ratings.
WSJ index	The Wall Street Journal climate change news index, a standardized attention index constructed in Engle et al. (2020) .

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

Ricardo Correa, Ai He, Christoph Herpfer and Ugur Lel

IA.1. Anecdotal evidence

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

In the last column of Appendix Table [IA.1](#), we report specific natural disasters mentioned in the context of climate change. Four banks mention specific disasters, with all of them mentioning hurricanes and/or storms. In addition, both Bank of America and JP Morgan Chase reference the risk of wildfires, and JP Morgan Chase mentions floods. In 2010, the only bank mentioning a specific disaster is SunTrust, a bank operating mostly in the Southeast, which mentions hurricanes.

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

1. Quotes from JPMorgan Chase 2019 10-K:

“JPMorgan Chase operates in many regions, countries and communities around the world where its businesses, and the activities of its clients and customers, could be disrupted by climate change. Potential physical risks from climate change may include:

- altered distribution and intensity of rainfall
- prolonged droughts or flooding
- increased frequency of wildfires
- rising sea levels
- rising heat index

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

2. Quotes from Bank of America's 2018 carbon disclosure project report:
"There is scientific consensus that flood risks are increasing in many regions due to climate change. [...] **We conduct an annual assessment of physical risks to our facilities from factors including severe weather, wildfires and flooding.**"
3. Quotes from Citi's 2019 10-K:
"**Climate change presents immediate and long-term risks to Citi and to its clients and customers, with the risks potentially increasing over time.** Climate risk can arise from physical risks (risks related to the physical effects of climate change) [...] **Citi's Environmental and Social Risk Management Policy incorporates climate risk assessment for credit underwriting purposes.**"
4. Quotes from Goldman Sachs' 2019 10-K:
"Climate change may cause extreme weather events that disrupt operations at one or more of our primary locations, which may negatively affect our ability to service and interact with our clients, and also may adversely affect the value of our investments, including our real estate investments. **Climate change may also have a negative impact on the financial condition of our clients, which may decrease revenues from those clients and increase the credit risk associated with loans** and other credit exposures to those clients."
5. Quotes from U.S. Bancorp' 2019 10-K:
"[...] **the force and frequency of natural disasters are increasing as the climate changes.**"
6. Quotes from Truist's 2018 10-K:
"[BB&T's operations and customers] could be adversely impacted by such events in those regions, **the nature and severity of which may be impacted by climate change** and are difficult to predict. These and other unpredictable natural disasters could have an adverse effect on BB&T in that such events could materially disrupt its operations or the ability or willingness of its customers to access the financial services offered by BB&T"
7. Quotes from PNC's 2019 10-K:
"Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] **we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans.**"
8. Quotes from TD Bank's 2019 10-K:
"Climate change risk has emerged as one of the top environmental risks for the Bank as extreme weather events, shifts in climate norms, and the global transition to a low carbon economy risks increase and evolve."
9. Quotes from Deutsche Bank's 2018 White Paper on Climate Change:
"We believe investors have no place to hide when it comes to the effects of physical climate change since even if emissions were cut to zero tomorrow, **society will still face intensifying extreme weather events over the next several decades.** [...] **Perhaps the most telling metric of a company's climate risk is the location of its assets and their exposure to changing extreme weather patterns.** The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks. [...] **Financial risk can go beyond recovering from an extreme weather event. Even a company**

that was not directly affected might be financially impacted. For example, through a gradual increase in its operational expenses due to rising insurance costs, a default in bank loans or other debt, or at a more macro-level, lower consumption levels.”

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

1. Quotes from Standard and Poor’s 2017 climate change report:
“We know that **climate change will increase the incidence and severity of weather events, both chronic and acute, such as hurricanes and droughts.** [...] Severe weather conditions lead to flooding of a large part of the construction site at the end of December 2015 and beginning of January 2016. [...] On Feb. 14, 2017, we lowered the Aberdeen Roads (Finance) plc rating to ‘BBB+’ from ‘A-’ [...]”
2. Quotes from Moody’s 2020 research note on U.S. utilities:
“As **climate change increases the frequency and severity of extreme weather events, anticipation of these hazards will be increasingly reflected in the capital investment programs of utilities.**”
3. Quotes from Moody’s 2017 research note on U.S. state and local government bonds:
“The report differentiates between climate trends, which are a longer-term shift in the climate over several decades, versus **climate shock, defined as extreme weather events like natural disasters, floods, and droughts which are exacerbated by climate trends.** Our credit analysis considers the effects of climate change when we believe a meaningful credit impact is highly likely to occur and not be mitigated by issuer actions, even if this is a number of years in the future.”

Quotes from United States Fourth National Climate Assessment:

1. “Observations show an increase in the severity, extent, and/or frequency of multiple types of extreme events. Heatwaves have become more common and severe in the West since the 1980s (high confidence). Drought risk has been increasing in the Southwest over the past century (very high confidence), while at the same time rainfall has become more extreme in recent decades, especially east of the Rockies (very high confidence). Hurricanes have been intensifying more rapidly since the 1980s (high confidence) and causing heavier rainfall and higher storm surges (high confidence). More frequent and larger wildfires have been burning in the West in the past few decades due to a combination of climate factors, societal changes, and policies (very high confidence).”
2. “The National Oceanic and Atmospheric Administration estimates that **the United States has experienced 44 billion-dollar weather and climate disasters since 2015** (through April 6, 2018), incurring costs of nearly \$400 billion.”
3. “**Since 1980, the number of extreme weather-related events per year costing the American people more than one billion dollars per event has increased significantly (accounting for inflation), and the total cost of these extreme events for the United States has exceeded \$1.1 trillion.**”
4. The report specifically mentions hurricanes, floods, droughts and wildfires, as well as tornadoes and heat waves.

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

1. Quotes from United Nations Environment Programme Finance Initiative 2018 Navigating a New Climate Report:

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

IA.2. Evidence on disasters and climate change

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

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

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

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

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

For hurricanes:

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

For floods:

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

The evidence on wildfires comes to a similar conclusion:

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

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

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

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

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

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

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

B. The perception of market participants linking disasters and climate change

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

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

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

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

These exercises demonstrate that the general public, and hence by extension likely market participants, pay substantial attention to the link between climate change and hurricanes, fires, and floods. There is no evidence of attention to climate change increasing the severity of winter weather.³²

³²In separate results, as an alternative, we directly compare (*"climate change" "hurricanes"*) to (*"climate change" "winter storm"*). We find that the aggregate search interest for winter storms is only 1.8% of that for hurricanes during 2004 to 2020, with the maximum search interest for winter storms never exceeding 2% of the maximum search interest for hurricanes. Throughout the sample, (*"climate change" "winter storm"*) has zero search interest until November 2011. We never find any search interest at all for (*"climate change" "winter weather"*) or (*"climate change" "blizzard"*).

IA.3. Internet appendix figures

Figure IA.1: Dynamics of price reaction in the secondary market

This figure presents the dynamics of effects of indirect hits from climate change-related disasters on the log of daily average quote prices in the loan secondary market over time. The sample includes existing loans' daily average quotes in 12 weeks before or 16 weeks after a hurricane hit, but excludes loans to firms that are directly affected by a major hurricane. Indirect hits are defined as in our main specification. Vertical lines represent 90% confidence intervals clustered by loans.

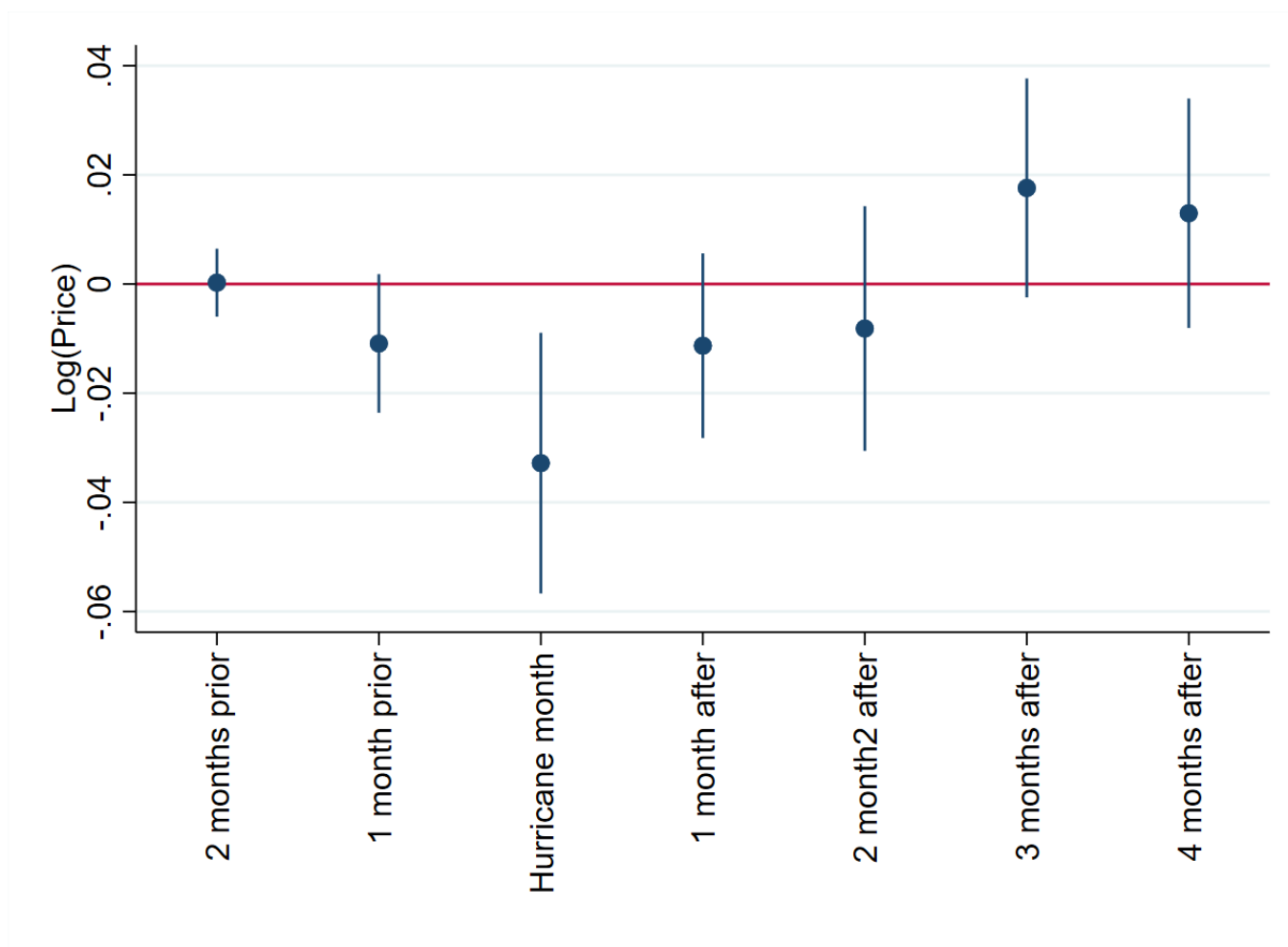
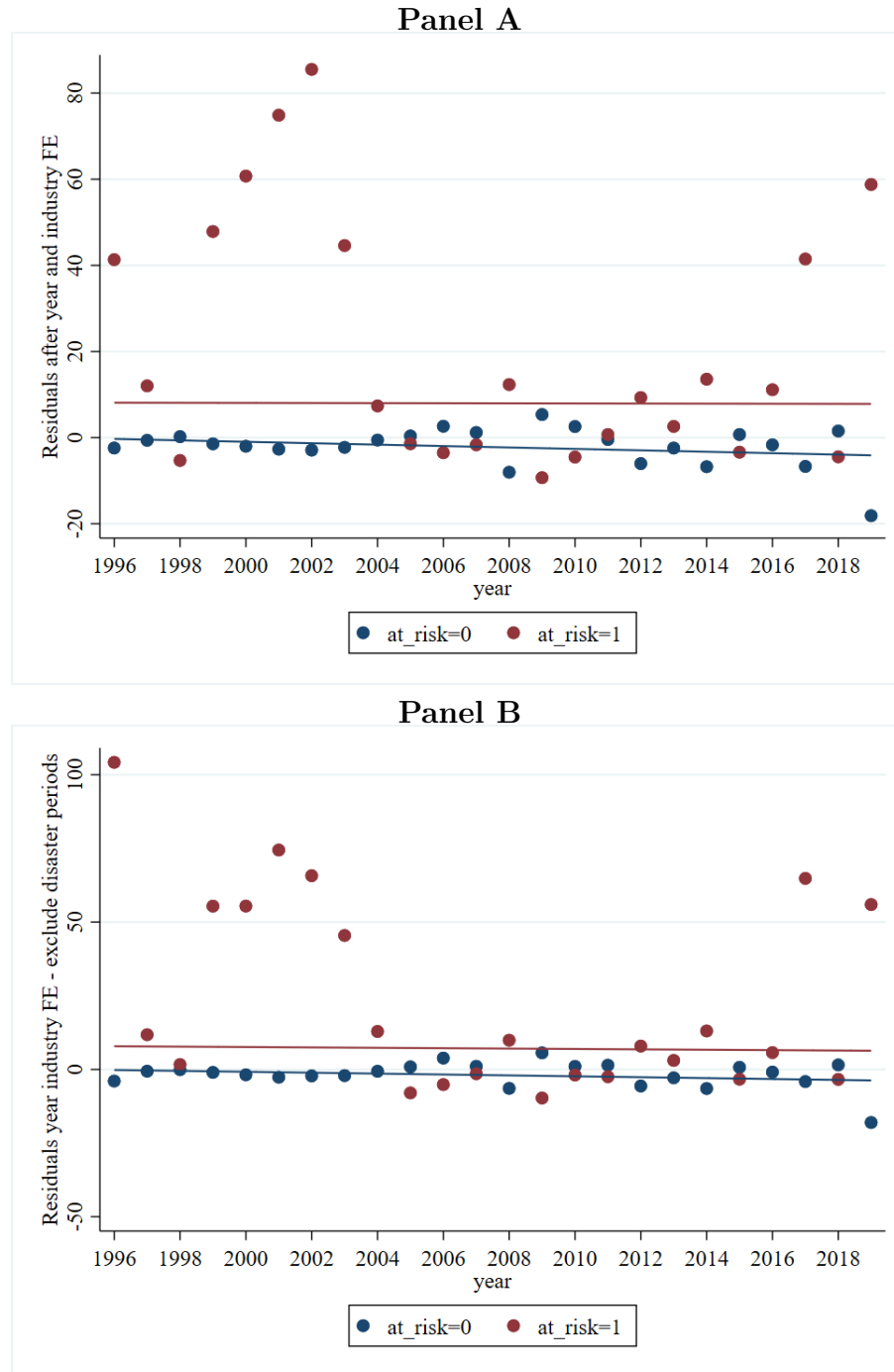


Figure IA.2: Spread over time for at-risk borrowers (residuals)

This figure presents the development of residual interest rates for borrowers at-risk and not-at-risk of hurricanes in levels. Residuals are obtained from regressions including all firm level accounting variables from our main specification, as well as industry and year fixed effects. Panel A is estimated for the entire sample, panel B residuals are obtained only from loans take out during quarters without recent disasters.



IA.4. Internet appendix tables

Table IA.1: Climate change-related disasters in banks' 10-K filings

This table reports a summary of the degree to which the 10 largest U.S. banks by assets mention climate change in their 2019 and 2010 annual reports in Panel A and B, respectively. The column "climate disasters" reports if these filings mention severe weather or natural disasters in the context of climate change broadly. The second column, "worsening trend" reports if the filings mention a potential increase in severity of these disasters due to climate change. The final column, "specific disasters", reports which specific types of severe weather are mentioned in this context, if any.

Panel A: 2019			
Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	Yes	Yes	Flooding, wildfire, heat, storm
Bank of America	Yes	Yes	Fire, hurricanes
Citi	Yes	Yes	None
Wells Fargo	Yes	No	Hurricanes
Goldman Sachs	Yes	Yes	None
Morgan Stanley	Yes	No	None
U.S. Bancorp	Yes	Yes	None
Truist	Yes	Yes	Hurricanes, storms
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

Panel B: 2010			
Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	No	No	None
Bank of America	No	No	None
Citi	No	No	None
Wells Fargo	Yes	No	None
Goldman Sachs	Yes	No	None
Morgan Stanley	Yes	No	None
U.S. Bankcorp	Yes	Yes	None
Truist (Suntrust)	Yes	Yes	Hurricanes
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

Table IA.2: Other loan terms

This table reports regressions of other loan terms on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. The outcomes in Columns 1 to 4 are the natural logarithm of the loan amount, the natural logarithm of loan maturity, an indicator for whether a loan is a revolver (as opposed to a term loan) and an indicator for the presence of financial covenants, respectively. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. Banker data is from [Herpfer \(2021\)](#). All variables are explained in Appendix [A.1](#). Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Log(amount)	Log(maturity)	Revolver	Covenant
	(1)	(2)	(3)	(4)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	-0.209* (0.114)	-0.105 (0.072)	0.027 (0.038)	-0.057 (0.060)
<i>Indirect hurricane</i>	0.109** (0.045)	-0.036 (0.025)	-0.004 (0.017)	-0.017 (0.025)
<i>Recent hurricane</i>	0.018 (0.045)	0.015 (0.019)	-0.046*** (0.013)	0.035 (0.021)
<i>N</i>	21262	21262	21262	21262
<i>R</i> ²	0.782	0.577	0.540	0.539
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

Table IA.3: Climate disasters and future direct risk

This table reports regressions of measures of direct hurricane disaster hits on previous indirect hits. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and month. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Full Sample			
	Direct hit	Direct hit large	Direct hit cont.
	(1)	(2)	(3)
<i>Previous indirect hit</i>	-0.001 (0.012)	-0.002 (0.007)	-0.005 (0.043)
<i>N</i>	164020	164020	164020
<i>R</i> ²	0.513	0.226	0.451
Firm FE	Yes	Yes	Yes
Year month FE	Yes	Yes	Yes

Panel B: Post 2011			
	Direct hit	Direct hit large	Direct hit cont.
	(1)	(2)	(3)
<i>Previous indirect hit</i>	-0.084 (0.073)	-0.059 (0.055)	-0.294 (0.266)
<i>N</i>	29367	29367	29367
<i>R</i> ²	0.467	0.239	0.420
Firm FE	Yes	Yes	Yes
Year month FE	Yes	Yes	Yes

Table IA.4: Climate disasters and future direct risk County Level: dynamics around hurricanes

This table is similar to [Dessaint and Matray \(2017\)](#) (DM) table 11, with previous indirect hurricane hit from one quarter to two years at the county level as the independent variable and future hit as the dependent variable. Parentheses contain standard errors double clustered by county and quarter. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Full sample						
	Hit					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Indirect hurricane 1q</i>	-0.052 (0.033)					
<i>Indirect hurricane 2q</i>		-0.029 (0.018)				
<i>Indirect hurricane 3q</i>			-0.017 (0.011)			
<i>Indirect hurricane 4q</i>				-0.025 (0.019)		
<i>Indirect hurricane 1y</i>					-0.060 (0.040)	
<i>Indirect hurricane 2y</i>						-0.054 (0.038)
<i>N</i>	265776	265776	265776	265776	265776	265776
<i>R</i> ²	0.204	0.198	0.197	0.197	0.206	0.204
Year quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County-season FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Post 2011						
	Hit					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Indirect hurricane 1q</i>	-0.025 (0.012)					
<i>Indirect hurricane 2q</i>		-0.015 (0.012)				
<i>Indirect hurricane 3q</i>			-0.007 (0.004)			
<i>Indirect hurricane 4q</i>				-0.011 (0.009)		
<i>Indirect hurricane 1y</i>					-0.049 (0.033)	
<i>Indirect hurricane 2y</i>						-0.033 (0.023)
<i>N</i>	63280	63280	63280	63280	63280	63280
<i>R</i> ²	0.232	0.230	0.229	0.229	0.238	0.233
Year quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County-season FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.5: Climate disasters and future direct risk County Level: 16 large hurricanes

This table is similar to [Dessaint and Matray \(2017\)](#) (DM) table 11, with previous indirect hurricane hit from one quarter to two years at the county level as the independent variable and future hit as the dependent variable. We only focus on 16 large hurricanes in this table. Parentheses contain standard errors double clustered by firm and month. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Hit					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Indirect hurricane 1q</i>	-0.051 (0.034)					
<i>Indirect hurricane 2q</i>		-0.029 (0.018)				
<i>Indirect hurricane 3q</i>			-0.017 (0.011)			
<i>Indirect hurricane 4q</i>				-0.025 (0.019)		
<i>Indirect hurricane 1y</i>					-0.060 (0.040)	
<i>Indirect hurricane 2y</i>						-0.054 (0.039)
<i>N</i>	265776	265776	265776	265776	265776	265776
<i>R</i> ²	0.204	0.199	0.198	0.198	0.207	0.204
Year quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County-season FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.6: Climate disasters and future direct risk (flood and fire)

This table reports regressions of measures of direct hurricane disaster hits on previous indirect hits. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and month. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Floods			
	Direct hit	Direct hit large	Direct hit cont.
	(1)	(2)	(3)
<i>Previous indirect hit flood</i>	-0.085** (0.017)	-0.047** (0.013)	-0.297** (0.062)
<i>N</i>	164020	164020	164020
<i>R</i> ²	0.326	0.196	0.309
Firm FE	Yes	Yes	Yes
Year month FE	Yes	Yes	Yes

Panel B: Fire			
	Direct hit	Direct hit large	Direct hit cont.
	(1)	(2)	(3)
<i>Previous indirect hit fire</i>	-0.017 (0.015)	-0.007 (0.014)	-0.057 (0.058)
<i>N</i>	164020	164020	164020
<i>R</i> ²	0.262	0.189	0.252
Firm FE	Yes	Yes	Yes
Year month FE	Yes	Yes	Yes

Table IA.7: Climate disasters and future county-level direct disaster damage: hurricane

This table reports county-level regressions of measures of direct hurricane disaster damages on previous indirect hits. We use three distinct measures of damages: total property damages at the county level, damage adjusted for price changes, and damages per capita. Parentheses contain standard errors double clustered by county and quarter. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Full sample				
	Property dmg.	Property dmg. (inf. adj.)	Property dmg. per capita (inf. adj.)	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit cumu</i>	0.211 (0.168)	0.055 (0.232)	-0.012 (0.010)	
<i>lag_Previous indirect hit cumu</i>				-0.013 (0.010)
<i>N</i>	715333	715333	715333	712169
<i>R</i> ²	0.056	0.053	0.053	0.053
County-season FE	Yes	Yes	Yes	Yes
Year qrt FE	Yes	Yes	Yes	Yes
Panel B: Post 2011				
	Property dmg.	Property dmg. (inf. adj.)	Property dmg. per capita (inf. adj.)	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit cumu</i>	4.695** (1.066)	7.775** (1.757)	0.311** (0.059)	
<i>lag_Previous indirect hit cumu</i>				0.195* (0.069)
<i>N</i>	63242	63242	63242	63240
<i>R</i> ²	0.236	0.234	0.227	0.227
County-season FE	Yes	Yes	Yes	Yes
Year qrt FE	Yes	Yes	Yes	Yes

Table IA.8: Climate disasters and future county-level direct disaster damage: flood

This table reports county-level regressions of measures of direct flood disaster damages on previous indirect hits. We use three distinct measures of damages: total property damages at the county level, damage adjusted for price changes, and damages per capita. Parentheses contain standard errors double clustered by county and quarter. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Full sample				
	Property dmg.	Property dmg. (inf. adj.)	Property dmg. per capita (inf. adj.)	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit cum flood</i>	0.349 (0.173)	0.601 (0.445)	-0.005 (0.014)	
<i>lag_Previous indirect hit cum flood</i>				0.005 (0.006)
<i>N</i>	358441	358441	358441	357763
<i>R</i> ²	0.097	0.090	0.115	0.082
County-season FE	Yes	Yes	Yes	Yes
Year qrt FE	Yes	Yes	Yes	Yes
Panel B: Post 2011				
	Property dmg.	Property dmg. (inf. adj.)	Property dmg. per capita (inf. adj.)	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit cum flood</i>	-4.352 (3.252)	-6.755 (3.618)	-0.111 (0.156)	
<i>lag_Previous indirect hit cum flood</i>				-0.065 (0.252)
<i>N</i>	22449	22449	22449	22242
<i>R</i> ²	0.369	0.371	0.398	0.322
County-season FE	Yes	Yes	Yes	Yes
Year qrt FE	Yes	Yes	Yes	Yes

Table IA.9: Climate disasters and future county-level direct disaster damage: wildfire

This table reports county-level regressions of measures of direct wildfire disaster damages on previous indirect hits. We use three distinct measures of damages: total property damages at the county level, damage adjusted for price changes, and damages per capita. Parentheses contain standard errors double clustered by county and quarter. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Full sample				
	Property dmg.	Property dmg. (inf. adj.)	Property dmg. per capita (inf. adj.)	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit cum fire</i>	0.277 (0.204)	0.614 (0.410)	0.003 (0.010)	
<i>lag_Previous indirect hit cum fire</i>				0.007 (0.006)
<i>N</i>	358441	358441	358441	357763
<i>R</i> ²	0.097	0.090	0.115	0.082
County-season FE	Yes	Yes	Yes	Yes
Year qrt FE	Yes	Yes	Yes	Yes

Panel B: Post 2011				
	Property dmg.	Property dmg. (inf. adj.)	Property dmg. per capita (inf. adj.)	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit cum fire</i>	1.662 (6.216)	2.505 (9.912)	-0.020 (0.163)	
<i>lag_Previous indirect hit cum fire</i>				0.020 (0.139)
<i>N</i>	22449	22449	22449	22242
<i>R</i> ²	0.369	0.371	0.398	0.322
County-season FE	Yes	Yes	Yes	Yes
Year qrt FE	Yes	Yes	Yes	Yes

Table IA.10: Time varying attention to climate change and rates - Google trends data

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

	Spread		
	(1)	(2)	(3)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	-21.277 (26.132)	4.436 (12.620)	16.213 (13.994)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Google trends index</i>	2.331 (1.320)		
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Above median Google trends</i>		61.634** (22.167)	
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Medium tercile Google trends</i>			21.959 (47.056)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i> $\times$ <i>Top tercile Google trends</i>			46.067** (18.472)
<i>N</i>	9472	9316	9472
<i>R</i> ²	0.777	0.777	0.777
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Lower interactions	Yes	Yes	Yes

Table IA.11: Time varying attention to climate change and rates - Reuters news data

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

	Spread		
	(1)	(2)	(3)
<i>Indirect hurricane × Recent hurricane</i>	17.329 (10.174)	8.662 (13.987)	-1.541 (19.240)
<i>Indirect hurricane × Recent hurricane × News attention index</i>	19.025* (10.495)		
<i>Indirect hurricane × Recent hurricane × Above median news attention index</i>		22.604 (20.516)	
<i>Indirect hurricane × Recent hurricane × Medium tercile news attention index</i>			-1.876 (39.305)
<i>Indirect hurricane × Recent hurricane × Top tercile news attention index</i>			47.311* (25.392)
<i>N</i>	14979	14979	14979
<i>R</i> ²	0.770	0.770	0.770
Bank × Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Lower interactions	Yes	Yes	Yes

Table IA.12: Pricing of climate change-related disasters with different characteristics

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. *Recent hurricane*_{>\$100bn}, *Recent hurricane*_{total hit counties top in past 10 years}, and *Recent hurricane*_{total first hit counties top in past 10 years} indicate the hurricane as “novel”, respectively, signaling by the total losses exceeding \$100 billion, the total number of counties hit is in top in the past 10 years, or the total number of counties which are first hit by a hurricane is in the past 10 years. 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)
<i>Indirect hurricane</i> × <i>Recent hurricane</i> _{>\$100bn}	31.022* (15.993)		
<i>Indirect hurricane</i> × <i>Recent hurricane</i> _{total hit counties top in past 10 years}		77.734*** (27.378)	
<i>Indirect hurricane</i> × <i>Recent hurricane</i> _{total first time hit counties top in past 10 years}			62.991** (29.260)
<i>Indirect hurricane</i>	4.292* (2.288)	4.291* (2.287)	4.337* (2.296)
<i>Recent hurricane</i> _{>\$100bn}	-0.390 (4.453)		
<i>Recent hurricane</i> _{total hit counties top in past 10 years}		-1.676 (6.209)	
<i>Recent hurricane</i> _{total first time hit counties top in past 10 years}			6.966 (6.145)
<i>N</i>	21262	21262	21262
<i>R</i> ²	0.742	0.742	0.742
Bank × Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table IA.13: Placebo tests with neighboring counties

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

	Spread			
	(1)	(2)	(3)	(4)
<i>Indirect hurricane neighbor</i> $\times$ <i>Recent hurricane</i>	4.594 (7.998)	2.705 (9.111)	5.230 (8.695)	4.612 (8.746)
<i>Indirect hurricane neighbor</i>	-0.144 (3.985)	2.065 (3.954)	1.232 (3.836)	1.366 (3.850)
<i>Recent hurricane</i>	5.098 (4.156)	2.708 (4.127)	2.715 (3.830)	3.084 (3.817)
<i>N</i>	21262	21262	21262	21262
<i>R</i> ²	0.696	0.730	0.741	0.742
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table IA.14: Regional spillovers from neighboring counties

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

	Spread			
	(1)	(2)	(3)	(4)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	17.208** (7.738)	18.715** (8.377)	19.130** (8.622)	18.752** (8.487)
<i>Indirect hurricane</i>	3.049 (5.047)	3.136 (4.404)	3.552 (4.028)	3.480 (3.975)
<i>Recent hurricane</i>	3.063 (3.874)	0.308 (3.808)	0.706 (3.671)	1.037 (3.685)
<i>Operations neighbour counties</i>	21.369 (15.964)	11.583 (15.495)	9.027 (14.048)	8.416 (14.793)
<i>N</i>	21262	21262	21262	21262
<i>R</i> ²	0.696	0.730	0.741	0.742
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

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Table IA.15: Robustness: geographic proximity

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. The sample excludes loans to firms that are directly affected by the major hurricane, as well as those with any operations within 75, 100, 150, and 200 miles of a 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) (>75miles)	(2) (>100miles)	(3) (>150miles)	(4) (>200miles)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	22.622** (9.433)	21.866** (10.465)	32.862*** (11.161)	35.032** (15.974)
<i>Indirect hurricane</i>	3.294 (4.003)	3.258 (3.965)	3.252 (4.023)	2.695 (3.994)
<i>Recent hurricane</i>	-2.301 (4.001)	-1.922 (4.216)	-4.755 (4.395)	-2.811 (4.439)
<i>N</i>	20702	20616	20350	20174
<i>R</i> ²	0.747	0.747	0.745	0.746
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

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Table IA.16: Bank disaster exposures and interest rate spreads

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

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

Table IA.17: Robustness: seasonality, industry, and state controls

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

	Spread				
	(1)	(2)	(3)	(4)	(5)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	21.467** (8.999)	26.009*** (9.126)	27.190* (15.693)	29.346* (17.046)	36.793* (19.018)
<i>Indirect hurricane</i>	3.390 (4.167)	1.394 (3.570)	2.279 (3.452)	1.817 (3.904)	-0.462 (4.402)
<i>Recent hurricane</i>	0.368 (3.828)	-5.416 (6.348)	-6.664 (7.426)	-8.583 (7.152)	-14.999 (10.774)
<i>N</i>	20463	21260	20797	20795	19983
<i>R</i> ²	0.752	0.767	0.844	0.859	0.865
Bank $\times$ Year FE	No	Yes	Yes	Yes	No
Bank $\times$ Year-Hurricane-Season FE	Yes	No	No	No	Yes
Industry $\times$ Quarter FE	No	Yes	No	Yes	Yes
State $\times$ Quarter FE	No	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes

Table IA.18: Hurricanes - excluding firms with any type of direct disaster damage

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

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

Table IA.19: Robustness: Rates and climate change-related disasters - bank-by-quarter fixed effects

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

	Spread			
	(1)	(2)	(3)	(4)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	24.990** (9.762)	24.794** (10.385)	24.322** (10.494)	23.896** (10.327)
<i>Indirect hurricane</i>	2.332 (5.056)	2.459 (4.695)	2.259 (4.342)	2.216 (4.314)
<i>Recent hurricane</i>	-2.399 (6.662)	-2.830 (5.824)	-0.748 (5.750)	-0.103 (5.761)
<i>N</i>	19022	19022	19022	19022
<i>R</i> ²	0.725	0.757	0.767	0.768
Bank $\times$ Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table IA.20: Robustness: Rates and different types of natural disasters - bank-by-quarter fixed effects

This table presents results from regressions of loan spread (in basis points) on the interaction of borrowers' indirect disaster exposure indicator with the occurrence of a major disaster in the preceding three months. The type of disasters changes across columns. The tests are similar to the ones in Table III. Standard errors double clustered by firm and year are reported in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent level, respectively.

Panel A: Climate change-related natural disasters				
	Spread			
	(1)	(2)	(3)	
	Hurricane	Flooding	Wildfire	
<i>Indirect disaster</i> $\times$ <i>Recent disaster</i>	23.896** (10.327)	11.428** (4.688)	13.122* (7.161)	
<i>Indirect disaster</i>	2.216 (4.314)	-1.450 (3.768)	-2.320 (3.935)	
<i>Recent disaster</i>	-0.103 (5.761)	-4.014 (4.435)	1.829 (5.588)	
<i>N</i>	19022	16850	19413	
<i>R</i> ²	0.768	0.800	0.781	
Bank $\times$ Quarter FE	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	
Loan controls	Yes	Yes	Yes	
Firm controls	Yes	Yes	Yes	
Panel B: Non-climate change-related natural disasters				
	Spread			
	(1)	(2)	(3)	(4)
	Earthquake (USGS)	Earthquake (hit)	Earthquake (abroad)	Winter weather
<i>Indirect disaster</i> $\times$ <i>Recent disaster</i>	-2.751 (7.963)	-16.662 (12.428)	1.331 (4.792)	-2.333 (7.491)
<i>Indirect disaster</i>	-6.391 (5.667)	-0.909 (4.369)	-7.236 (6.135)	-2.209 (3.809)
<i>Recent disaster</i>	6.304 (7.186)	6.965 (6.884)	7.721** (3.312)	-6.667 (6.934)
<i>N</i>	20914	21688	20914	20947
<i>R</i> ²	0.762	0.762	0.762	0.763
Bank $\times$ Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

Table IA.21: Compare the effect of disasters with similar damages: flooding, wildfire, and winter weather
This table reports regressions of loan spread (in basis points) on borrowers' indirect disaster indicator with the occurrence of the same type of disasters. For flooding and wildfire in column (1) and (2), we only consider those that caused similar dollar-measured damages compared with winter weather. We exclude loans taken out by a firm with any type of direct disaster damage in a given quarter. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1) Flooding	(2) Wildfire	(3) Winter Weather
<i>Indirect disaster</i> $\times$ <i>Recent disaster</i>	9.658** (4.502)	12.249* (6.590)	1.389 (7.613)
<i>Indirect disaster</i>	-1.049 (4.300)	-1.772 (3.727)	-2.624 (3.471)
<i>Recent disaster</i>	-7.494** (3.271)	-5.668 (3.642)	10.118 (7.758)
<i>N</i>	18342	21380	23252
<i>R</i> ²	0.772	0.755	0.736
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table IA.22: Robustness: clustering standard error by disasters

This table presents results from regressions of loan spread (in basis points) on the interaction of borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the preceding three months. The sample excludes loans to firms that are directly affected by the major hurricane. Loan-level controls include loan maturity, loan type and covenant indicators. Firm-level controls include borrower's log(total asset), ROA, debt over asset ratio, and borrower's direct exposure to non-hurricane disasters, if any. Parentheses contain standard errors double clustered by natural disaster and year in columns (1) and (3), or by natural disaster and firm in columns (2) and (4). *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Panel A: The full sample				
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.778** (8.247)	18.778** (8.507)	21.596** (9.929)	21.596** (9.106)
<i>Indirect hurricane</i>	3.467*** (0.892)	3.467** (1.224)	3.336** (1.148)	3.336** (1.216)
<i>Recent hurricane</i>	1.178 (3.023)	1.178 (3.022)	17.740*** (2.575)	17.740*** (1.656)
<i>N</i>	21262	21262	21262	21262
<i>R</i> ²	0.742	0.742	0.743	0.743
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Disaster FE	No	No	Yes	Yes
SE two-way clustered by	Disaster & Year	Disaster & Firm	Disaster & Year	Disaster & Firm
Panel B: Exclude Hurricane Katrina and Hurricane Sandy				
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.517* (9.831)	18.517* (9.297)	24.738* (11.629)	24.738** (9.535)
<i>Indirect hurricane</i>	3.513** (1.196)	3.513*** (1.150)	3.341** (1.324)	3.341*** (1.116)
<i>Recent hurricane</i>	0.113 (3.527)	0.113 (3.103)	16.900*** (2.643)	16.900*** (1.394)
<i>N</i>	20903	20903	20903	20903
<i>R</i> ²	0.743	0.743	0.744	0.744
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Disaster FE	No	No	Yes	Yes
SE two-way clustered by	Disaster & Year	Disaster & Firm	Disaster & Year	Disaster & Firm

Table IA.23: Robustness: changing the disaster firm exclusion window

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane indicator with the occurrence of hurricanes. We exclude loans taken out by a firm that are affected by hurricanes within 9, 12, 15, or 18 months in column (1), (2), (3), or (4), respectively. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1) 9 months	(2) 12 months	(3) 15 months	(4) 18 months
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	16.935** (7.719)	17.925** (8.593)	26.063** (10.325)	41.256*** (11.540)
<i>Indirect hurricane</i>	2.369 (4.926)	3.281 (5.794)	0.942 (5.716)	0.687 (6.459)
<i>Recent hurricane</i>	1.095 (3.726)	1.312 (4.178)	1.564 (4.605)	-1.322 (4.795)
<i>N</i>	16054	14086	12711	11645
<i>R</i> ²	0.757	0.760	0.766	0.775
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

Table IA.24: Robustness: define treatment firms with expanding windows

This table reports regressions of loan spread (in basis points) on borrowers' indirect hurricane indicator with the occurrence of hurricanes. The sample excludes loans to firms that are directly affected by the major hurricane. *Indirect hurricane* are defined following the similar way in Section III but based on a 15-year rolling window in Column (1), a 20-year rolling window in Column (2), or the full disaster records from 1980 in Column (3), to the month of *Recent hurricane*. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread		
	(1) 15-year	(2) 20-year	(3) Since 1980
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	19.149* (10.878)	19.386* (10.626)	18.865* (10.346)
<i>Indirect hurricane</i>	2.333 (4.266)	2.878 (4.150)	4.883 (4.357)
<i>Recent hurricane</i>	0.788 (3.192)	0.773 (3.206)	0.613 (3.214)
<i>N</i>	21262	21262	21262
<i>R</i> ²	0.742	0.742	0.742
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Table IA.25: Robustness: Rates and climate change-related disasters - alternative treatment definitions

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

	Spread			
	(1)	(2)	(3)	(4)
<i>Indirect hurricane general</i> $\times$ <i>Recent hurricane</i>	18.772* (9.550)			
<i>Indirect hurricane general continuous</i> $\times$ <i>Recent hurricane</i>		4.536** (2.020)		
<i>Indirect hurricane continuous</i> $\times$ <i>Recent hurricane</i>			4.751** (2.066)	
<i>Any indirect hurricane</i> $\times$ <i>Recent hurricane</i>				17.142** (7.152)
<i>N</i>	21262	21262	21262	21262
<i>R</i> ²	0.743	0.742	0.742	0.742
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	Yes	Yes

Table IA.26: Climate disasters and rates (operation & employment & sales weighted operations)
This table reports regressions of loan spread (in basis points) on borrowers’ indirect climate change-related disaster indicator with the occurrence of major hurricanes. We calculate firms’ exposure to climate hurricane prone areas comprehensively using operation-, employment-, and sales-weights, thus “Indirect hurricane” is a flag for a firm if its operation-weighted, employment-weighted, and sales-weighted exposures are all in the top quintile of the cumulative distribution. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Spread			
	(1)	(2)	(3)	(4)
<i>Indirect hurricane</i> $\times$ <i>Recent hurricane</i>	18.537** (8.247)	17.391* (9.135)	16.737* (8.994)	16.338* (8.912)
<i>Indirect hurricane</i>	-1.656 (5.218)	-0.234 (4.793)	0.468 (4.499)	0.202 (4.453)
<i>Recent hurricane</i>	4.125 (3.761)	1.513 (3.715)	1.983 (3.677)	2.291 (3.660)
<i>N</i>	21262	21262	21262	21262
<i>R</i> ²	0.696	0.730	0.741	0.742
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table IA.27: Previous indirect hits and future financing outcomes

This table reports regressions of financing outcome variables at the firm-quarter level on firms' historical indirect hit records. Non-investment grade is an indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB). In columns (1) and (2), other debts are calculated as firms' quarterly debt net of syndicated loan issuance. In columns (3) and (4), the sample includes firms with loan issuance in non-hurricane periods. Loan maturity is the average value at the firm-quarter level. Firm-level controls including log(total asset), ROA, debt over asset ratio, and borrower's indirect exposure to climate disasters. Standard errors double clustered by firm and year are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Log(Other debts)		Loan Maturity	
	(1)	(2)	(3)	(4)
<i>Previous indirect hit count</i>	0.019*	0.020*	-0.002	0.015
	(0.010)	(0.011)	(0.018)	(0.019)
<i>Previous indirect hit count</i> $\times$ <i>Non-investment grade</i>		-0.006		-0.087***
		(0.011)		(0.031)
<i>N</i>	42044	42044	4540	4540
<i>R</i> ²	0.888	0.888	0.460	0.461
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

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