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

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**Abstract**

We investigate how corporate borrowing costs are affected by natural disasters related to climate change. We construct granular measures of borrowers' exposure to, and therefore risk associated with, various natural disasters. We then disentangle the direct effects of disasters from the effects of lenders updating their beliefs about the severity and frequency of future disasters. Following a climate change–related disaster, yields on loans of at-risk, yet unaffected borrowers spike both in the primary and secondary markets. These effects are amplified when attention to climate change is high, and there is no such effect from disasters that are not aggravated by climate change. Borrowers with the most extreme exposure to climate change and borrowers with the least ability to absorb adverse shocks suffer the highest increase in rates. Firms react by reducing investment and increasing their cash reserves.

**JEL Classifications:** G21, Q51, Q54

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# 1 Introduction

Climate change can have potentially devastating long-term economic effects (Stern, 2007), with the majority of climate change–related consequences expected towards the end of the century (Hong, Karolyi, and Scheinkman, 2020). However, the long delay before these effects fully impact the global economy can discourage actions to mitigate climate change–related risks, and the relevance of these risks from today's perspective depends heavily on discount rates (Nordhaus, 2010). As a result, large parts of the literature on climate change and financial markets have concentrated on long-lived assets such as real estate or equities (Giglio, Maggiori, and Stroebel, 2015; Murfin and Spiegel, 2020; Baldauf, Garlappi, and Yannelis, 2020), and focuses on estimating discount rates to capture long-run damages (Giglio, Maggiori, Rao, Stroebel, and Weber, 2018).

Our paper instead uses a novel channel through which climate change already shapes economic risks today even in comparatively short-lived assets, namely corporate loans. Specifically, we focus on the increased frequency and severity of certain extreme weather events. A key challenge in linking climate change to corporate debt funding is that the average loan maturity is only four years, while most climate change–related consequences are projected to peak towards the end of the 21st century. Consistent with this mismatch between the maturity of financial instruments and the long horizon of climate change, Addoum, Ng, and Ortiz-Bobea (2020) find no current effect of extreme temperatures on firms, and Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2019) find that investors have only very recently started to price projected long-term sea level rises in generally longer dated municipal bonds.

We focus on severe weather events or natural disasters, specifically hurricanes, which are already intensifying in severity and frequency because of climate change today.[1] These disasters are likely the first channel through which physical risks associated with climate change directly affects borrowers; therefore, they comprise a perfect laboratory to overcome the long-term horizon challenge of climate change (Giglio et al., 2018). Importantly, these

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

types of climate risks are already being priced by investors, as almost two-thirds of institutional investors surveyed by Krueger, Sautner, and Starks (2020) report that they expect the physical risks of climate change to affect their credit portfolios today or within two years. Beyond the impact of climate change on loan pricing, we also assess whether extreme weather events already affect firms' financial decisions such as investments and cash holdings. This would provide early evidence on the consequences of climate change dynamics on corporate actions.

The most straightforward approach to assess the effect of climate change-related natural disasters on firms' borrowing costs is to analyze the loan spreads charged by banks after borrowers are directly hit by disasters. While this approach would yield evidence on financial institutions' pricing of disaster risk (see Figure 1), it cannot disentangle the direct effect of the disaster on loan spreads, such as through disruptions of business operations and physical damage, from the updating in lender's expectation about the future frequency and severity of these disasters. In particular, measuring the direct reaction to disasters cannot account for changes in corporate exposure to affected regions (Nordhaus, 2010), meaning this estimation cannot disentangle the direct shocks of disasters from banks' indirect updating about climate change .

Instead, our identification strategy relies on observing changes in loan spreads for borrowers who are exposed to climate change–related disasters but not directly affected by a specific event. We refer to these firms as *indirectly affected* borrowers. This approach allows us to isolate lenders' updated expectations on the future severity of climate change–related events. The staggered aspect of disasters also mitigates the concern that results are driven by potentially omitted and coinciding events.

We find that following climate change–related disasters, banks charge higher spreads on loans to *indirectly affected* borrowers with recently high exposure to disasters. This effect varies from 19 basis points for hurricanes to about 8 basis points for wildfires and floods. These changes in loan spreads are economically sizable, as they represent about 5% to 10% of the unconditional spread in the sample. In our baseline specification, we focus on hurricanes, as they are widely observed, severe, and relatively frequent. Consistent with a nonlinear effect related to exposures, the impact on loan spreads is concentrated among borrowers with the largest indirect exposures to these natural disasters. Further, firms with higher credit risk ex ante experience greater hikes in loan spreads. This suggests that the change in loan spreads is strongly related to borrowers' creditworthiness.

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

This evidence on the link between climate-related risks and loan pricing is not completely surprising, as it is consistent with lenders' awareness of the threats that climate change poses to their loan portfolios. In recent regulatory filings, the 10 largest U.S. banks discuss the link between climate change and certain severe weather incidents, and 8 out of 10 banks mention that climate change (potentially) intensifies these disasters and poses a material risk to the creditworthiness of borrowers (see Appendix Table A.1). Lenders, credit rating agencies, and governments are aware of the threat of climate change–related disasters for loans.[2]

Our baseline work focuses on the primary market for syndicated loans, but we also find that climate risks are priced in the secondary market. In this market, we observe a 2.1% decline in loan prices following recent climate change–related natural disasters, providing evidence that climate change affects loan pricing beyond origination. This is important, as it suggests that a firms' decision to raise funds does not drive this observed increase in loan spreads. Moreover, this result suggests that investors beyond banks also price the climate risk embedded in these types of loans.[3]

After testing the effects on loan spreads, we assess whether climate risks force firms to adjust their investments. We find that bank-dependent firms reduce their investment by about one quarter of one percent, or about 15% relative to the sample mean. This finding provides further evidence that climate change–related risks may already

[2]For example, PNC Bank's 2019 10-K filing explicitly states, "Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans." Appendix A.2 provides a wide range of examples for this type of awareness of the link between climate change, disasters, and credit risk.

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

affect firms through their cost of funding.

In our empirical tests, we exploit detailed geographic exposure data on a large cross-section of U.S. borrowers from the National Establishment Time-Series (NETS) database in combination with the Spatial Hazard Events and Losses Database for the United States (SHELDUS). For each borrower, we construct measures of their exposure to various types of disasters, as a results of the geographic footprint of their operations. This setup allows us to measure not only the direct impact of disasters that affect borrowers but also borrowers' general exposure to certain types of disasters based on their operations in at-risk areas.

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

Natural disasters can conceivably affect firms by exerting a more widespread effect on the economy as a whole. To investigate whether our estimates truly reflect lenders' updating views about climate change–related disasters, we repeat our main analysis using disasters that are not related to climate change (i.e., earthquakes and winter weather). Borrowers with indirect exposure to these non–climate change disasters experience no changes in interest rates in either the primary or secondary loan market. Moreover, our estimates hold when we simultaneously estimate the effects of both climate change–related disasters and disasters unrelated to climate change. Consistent with banks learning about the severity of disasters, the reaction in loan spreads for indirectly affected firms is stronger for more severe disasters.

An additional concern might be that large-scale disasters (e.g., hurricanes, floods) ripple through the economy due to customer–supplier links (Barrot and Sauvagnat, 2016) and this effect may be more concentrated among firms that share similar exposure to disasters (i.e., similar geographical profiles) and for more widespread disasters (e.g., hurricanes) as opposed to localized disasters (e.g., tornadoes). Therefore, we conduct an additional test that directly controls for each borrower's exposure to disasters through their customer–supplier linkages. We find that our estimates are unaffected.

We explicitly control for lenders' exposure to directly affected borrowers to further rule out the possibility that our results are (a) driven by capital transfers between directly affected and indirectly affected borrowers or (b) driven by the widespread impact of major disasters on banks' balance sheets. Our findings that banks increase loan spreads to indirectly affected borrowers remains unchanged. These results are also robust to a wide range of alternative model specifications, variations in the size cutoff of disasters, various ways of quantifying corporate geographic exposure, variations in the definition of *affected borrowers*, controlling for the different seasonality and frequency of earthquakes and hurricanes, controlling for the cyclicality in lending to certain industries, and alternative measures of attention.

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

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

Another contribution is that we provide estimates on the credit risk costs that banks assign to natural disasters related to climate change. This assessment is crucial, as banks may be forced to enhance their risk-management practices related to climate risks if such events become more intense or more frequent. Relatedly, the finding that loan spread hikes around climate change–related natural disasters are transitory and driven significantly by attention to climate risks may have consequences from a regulatory perspective. This implies that banks may be inadequately provisioning for potential future climate change–related loan losses, and this can diminish banks' financial resilience and result in economy-wide adverse effects in the long term. Finally, we identify that climate change–related natural disasters can be used as a method to understand the impact of climate change on the pricing of short-lived assets.

## 2 Hypotheses development

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

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

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

One potential problem with this setup is that banks might also update their beliefs on the future exposure of borrowers to disasters (Nordhaus, 2010). Therefore, we contrast these results on climate change disasters with non–climate change disasters. We test:

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

Finally, we hypothesize that time-varying attention to climate change leads to fluctuations in the pricing of climate change disaster risk in the corporate loan market.

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

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

# 3 Data

## 3.1 Data on disasters

We obtain data on disasters from the Spatial Hazards Events and Losses Database for the United States (SHELDUS), which is a county-level natural hazard data set for the U.S. from 1960 to present. This database provides information on the date of an event, affected location (county and state) and the direct losses caused by the event (property and crop losses, injuries, and fatalities). These data are widely used in studies on the effect of natural disasters, including studies on bank lending (Cortés and Strahan, 2017). We include disasters in which the Governor declared a “state of emergency” with a formal request for Federal Emergency Management Agency (FEMA) funds to respond to the disaster. Thus, we include only relatively large disasters. We classify disasters as being related to climate change based on reports produced by the Intergovernmental Panel on Climate Change or IPCC (Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi, et al., 2017).[4] This report finds substantial evidence of a link between climate change and droughts, heat waves, and wildfires today. The report finds similarly strong evidence for a link between climate change and more severe Atlantic hurricanes as well as extreme precipitation. Therefore, we classify hurricanes, floods, and wildfires as climate change related. In our baseline specification, we focus on hurricanes as climate change–related disasters, as they are widely observed, severe, and relatively frequent. In Appendix 5, we show that our results hold for each of these disasters individually as well as a pooled estimation of them jointly.

We contrast our findings for climate change related disasters with those for earthquakes, which are disasters that are completely unrelated to climate change. The IPCC also finds that climate change leads do a reduction in the number of incidents of extreme low temperatures, which are coded as *winter weather* in SHELDUS. We, therefore, also conduct tests of winter weather as non-climate change–related disasters.[5] Among natural disasters, earthquakes are the most clearly unrelated to climate change. Therefore, our main specification uses only earthquakes as non–climate change disasters. As for climate change disasters, Appendix 5 provides tables that show the robustness of our results to considering also winter weather individually or pooled. Since earthquakes are rather infrequent in the U.S. and there have been few during our sample, we further run an additional robustness test using foreign earthquakes as shocks to attention to earthquakes in Appendix Table A.2.

We focus on large disasters with aggregate damages that exceed $100 million in 2019 constant dollars. We calculate each counties' exposure to each disaster within a rolling 10-year window. We then classify counties as *high-exposure* counties if they are in the top 10% of counties with respect to damages for a certain type of disaster within that window. Appendix Table A.8 shows that these effects are stronger when we limit ourselves to larger, more severe disasters.

### 3.2 Other data

We construct granular corporate geographic footprints to quantify each borrower's exposure to climate change disasters. Deutsche Bank, in its 2018 white paper, captures this intuition: "Perhaps the most telling metric of a

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

[5]While the evidence is strong that climate change reduces incidents of extreme low temperatures, the evidence is more mixed with respect to tornadoes, which also often result from hurricanes which increase in frequency and severity due to climate change. Interestingly, we find that the market prices tornadoes somewhere between disasters related to climate change and other unrelated disasters. This intermediate pricing could reflect this uncertainty.

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."[6]

We construct detailed geographic footprints of corporations using Dun and Bradstreet's National Establishment Time Series (NETS) data. We use the county-level data on the number of establishment locations to create a location-weighted measure of a company's exposure to each disaster type. To do so, we multiply each firm's fraction of establishments in each county by that county's exposure to disasters, arriving at an operations-weighted measure of a firm's exposure to disasters. We then classify a firm as *indirectly exposed* to each type of disaster (e.g., hurricanes) if its operations-weighted exposure to historically disaster-prone counties is in the top quintile of firms.[7]

We add syndicated loan data from Refinitiv's DealScan database, and obtain accounting data from Compustat. DealScan provides loan information at origination, including loan amount, loan maturity, and loan spread. We begin our sample from 1996 with the introduction of the SEC's mandatory electronic filing, including all loans in the United States that can be matched with NETS data on the borrower side. We also adjust loan amounts to the value of the dollar in 2019, using the GDP deflator of the Bureau of Economic Analysis. Syndicated loans have one or more lead arrangers and several participating lenders. A *lead lender* serves as an administrative agent who has a fiduciary duty to other syndicate members to provide timely information about the borrower, whereas *participating lenders* are passive investors whose main role is sharing the ownership of a loan. So, we restrict our analysis to lead lenders. Finally, firms might potentially be both directly and indirectly affected by a disaster. To avoid our results being driven by this overlap, we exclude all loans of those borrowers that have suffered from either hurricanes or earthquakes within 3 months before the loan origination.

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

[Table 1 here]

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

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

Panel A covers all matched loans in our sample. The median loan is a \$649.73 million (in 2019 U.S. dollar) credit package with a 5-year maturity and a 150.00 bp 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. The origination month of 10% of the loans falls within three months after a hurricane hit. Similarly, the origination month of 4% of the loans falls within three months after an earthquake hit.

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

# 4 Results

## 4.1 Empirical setup

As described in section 2, our main objective is to test for the impact of climate change–induced disasters on loan spreads. A naive approach to assess this relation is to estimate the impact of these natural disasters on loan spreads for firms *directly* exposed to such events. Figure 1 presents this analysis.

[Figure 1 here]

As presented in the figure, the impact of climate change-related disaster on loans spreads appears to exhibit a small and positive time trend. Compared to the time period of 1996 to 2001, loans issued by firms following a direct disaster hit carry an additional increase in spread by about 20 to 30 basis points from 2006 to 2019. This direct approach, however, does not allow us to disentangle changes in the magnitude of the direct effects of the disaster from the effect of the disasters becoming stronger.

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

To disentangle the direct effect of a natural disaster from the indirect effect of lenders learning about the increased risk of climate change–induced disasters, we do not draw inferences from firms that are actually hit by these events; instead, we draw inferences from firms that are at risk from climate change-related disasters but that do not experience any damages in a given disaster event.

Intuitively, our hypothesis is that banks learn about the increased severity of climate change disasters by observing them. 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 strikes Houston in 2017, this borrower is not directly affected by the damage. However, if the bank updates its prior expectations regarding the severity of hurricanes after observing Harvey, the bank will still charge a risk premium for the next loan granted to this hypothetical borrower in Florida. Formally, our econometric setup, in its most complete form, can be described by Equation 1 below:

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

The outcome variable of interest is the interest rate spread charged to borrower $i$ by bank $m$ in year $t$. Our main coefficient of interest is $\beta_1$. It measures the effect of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$, which is the interaction of our time-varying measure of firm $i$'s exposure to hurricanes with an indicator of a recent hurricane in the past quarter. We expect $\beta_1$ to be positive if banks update their prior expectations about the severity of climate change disasters after observing them.

Greater exposure to climate change disasters might reflect time-varying levels of riskiness (e.g., expansion into new markets). We therefore control for $Indirect\ hurricane_{i,t}$. The indicator *recent hurricane* takes the value of 1 if a climate change disaster has occurred within the 3 months before loan origination. Therefore, it is not absorbed in the year fixed effects. Since most of our sample firms have geographically far-flung operations, most severe natural disasters (e.g., hurricanes) have at least a small impact on many borrowers. We therefore drop all loans taken out by borrowers who are directly affected by a hurricane or earthquake in the quarter of the loan. We further add a direct control for the direct exposure to all other disasters.

Borrowers with more indirect exposure to hurricanes might be different from other borrowers on unobservable dimensions. Therefore, we include borrower fixed effects ($\alpha_i$), into our estimation. In effect, we compare two loans obtained by the same borrower: 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 absorb a number of alternative explanations, such as the geographic location of a firm's operation or the industry in which it operates.

Another potentially confounding channel is the bank internal–funding channel. Major disasters drain funds from banks, and the rising loan spreads for unaffected borrowers might reflect this internal-funding channel (Cortés and Strahan, 2017). We therefore include bank × year fixed effects ($\phi_{m,t}$) in our regressions.[8] Intuitively, this means we are comparing two borrowers from the same bank, in the same year, and the only difference between them is the borrower's indirect exposure to a recent climate change disaster. The within-lender-time comparison is central to our empirical strategy. To properly capture this effect, we include all borrower–lender pairs in our estimation if a loan has more than one lead lender. Finally, we include $X_{i,j,t}$, a vector that reflects a wide range of time-varying firm controls (e.g., size, profitability, debt-to-asset ratio) and loan controls (e.g., loan type, maturity, covenants).

## 4.2 Climate change and loan pricing

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

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

[Table 2 here]

The key coefficient in this specification is $\beta_1$, which is the effect the interaction between (a) our time-varying measure of firm $i$'s exposure to climate change disasters and (b) an indicator of a recent disaster of that type. In Column 1 of Table 2, the coefficient estimate of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ is 17.3 bp and is statistically significant at the 5% level. After a climate change disaster, banks raise interest rates spreads for unaffected borrowers with high exposure to this type of disaster. The economic magnitude of this effect is sizeable and comparable to a credit rating downgrade of about two notches.

Borrower fixed effects in this specification control for unobservable, borrower-level heterogeneity in loan prices. To avoid intra-bank capital transfers driving our results, we further control for Bank × year fixed effects, which means our inference effectively stems from comparing two borrowers of the same lender in the same year. Finally, we control for the degree to which each borrower is directly affected by climate change disasters.

In Column 2, we add loan-level controls for maturity, loan type, and the presence of financial covenants. Our main coefficient estimate remains economically and statistically very similar, at about 18.8 bp. The same is true when we replace these loan controls with firm-level control variables that capture time-varying firm-level credit quality in column 3. These controls include profitability, leverage, and credit rating. The estimate for $\beta_1$ in this setting is 19.2 basis points. Column 4 presents our most complete specification, which includes the full set of fixed effects, bank controls, and loan controls. The coefficient estimate of $\beta_1$ in this specification is about 18.8 bp.

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

One concern is that these estimates reflect banks updating their perception of disasters more generally and not climate change disasters in particular. Table 3 repeats the analysis from Table 2, but it replaces our measures of direct and indirect exposure to *hurricanes* with analogous measures for *non–climate change disasters*, i.e., earthquakes.[9]

[9] As described in Section 3, we follow the IPCC guidance when classifying disasters as climate change–related disasters or disasters not related to climate change. Our results are robust to variations in this definition, and we include regressions for each individual disaster in Appendix 5. All our results are robust to using each disaster individually as well as pooling climate change disasters and non–climate change disasters together.

[Table 3 here]

In Column 1, the estimated coefficient on $Indirect\ earthquake_{i,t} \times recent\ earthquake_t$. The coefficient estimate is statistically insignificant and actually -4.2 bp, in contrast to the positive coefficient on climate change disasters of about +18 bp. As we add the various controls for firm- and loan-level variables in Columns 2 to 4, the coefficient estimate on $\beta_1$ remains statistically insignificant and economically negligible throughout.

This result supports our interpretation of the results in Table 2. Climate change intensifies certain types of disasters over time. Banks observe this increase in severity and update the spread for at-risk borrowers accordingly. While non–climate change disasters are similarly devastating for borrowers, they do not intensify over time, thus banks already price them correctly in their loans. One potential concern could be that there were no major earthquakes inside the United States during our sample period, making comparisons between U.S. hurricanes and U.S. earthquakes difficult. We address this concern in Appendix Table A.2, where we replace domestic earthquakes with the thirteen most devastating global earthquakes (in terms of damages) during our sample period, and find again no effect on the risk premium charged for loans of at-risk, domestic firms.[10]

In an additional test, we rule out the possibility that our results are driven by the potential simultaneous occurrence of a climate change disaster and a non–climate change disaster. In Table 4, we simultaneously control for the effects of both climate change disasters (e.g., hurricanes) and non–climate change disasters (e.g., earthquakes).

[Table 4 here]

As in our main analysis, we find that the effect of climate change disasters on firms with general exposure to these disasters is associated with a statistically and economically large increase in interest rate spreads of about 17–19 bp, even after controlling for simultaneously occurring non–climate change disasters. As in the analysis in Table 3, the coefficient on $Indirect\ earthquake_{i,t} \times recent\ earthquake_t$ is small, negative, and statistically insignificant throughout all specifications.

These results support the idea that banks learn about the increasing severity of climate change disasters and increase the spreads charged to borrowers who are at risk for these disasters, consistent with *Hypothesis 1.* We

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

also find support for *Hypothesis 2*, as banks do not seem to price indirect exposures to natural disasters not associated with climate change.

## 4.3 Climate change is priced more severely for borrowers under financial stress

Increased borrower risk hurts banks mostly through the threat of default. A financially healthy borrower can weather the damage from a climate change disaster with no impact on their ability to repay their debt. In contrast, borrowers who are close to bankruptcy have the highest risk of defaulting on loans as a result of their exposure to a climate change disaster. If banks indeed price the increased risk from climate change disasters, the price reaction should be most pronounced among borrowers who are more at risk of bankruptcy. We empirically test this conjecture in Table 5 using two proxies for borrower risk.

[Table 5 here]

First, in Column 1, we estimate the most saturated model of Table 2, Column 4, and we interact $\textit{Indirect hurricane} \times \textit{Recent hurricane}$ with *market leverage*, firms' leverage level at the time of loan origination. As before, for ease of exposition, we do not tabulate the lower interactions and control variables of each regression. The interaction term $\textit{Indirect hurricane} \times \textit{Recent hurricane} \times \textit{market leverage}$ captures the differential effect of an indirect hurricane impact on firms with elevated credit risk. For ease of exposition, we normalize market leverage, such that the coefficient can be interpreted as the effect of a one standard deviation increase in leverage. Consistent with banks reacting more pronounced when borrowers are less financially stable, we find that the coefficient on the triple interaction is 25.2 bp, while the double interacting $\textit{Indirect hurricane} \times \textit{Recent hurricane}$ stays around 17.5 bp. The effect on highly leveraged borrowers is therefore more than twice as large as the effect in the overall sample. This result suggests that banks price climate change disaster risk mostly for at-risk borrowers.

One specific way through which natural disasters threaten firms' credit worthiness is through the threat of destroying physical assets, particularly as those can secure loans. In column 2, we estimate the triple interaction $\textit{Indirect hurricane} \times \textit{Recent hurricane} \times \textit{tangibility}$, where *tangibility* is the borrowers (normalized) tangibility of assets. Consistent with the threat to physical assets amplifying the effect of hurricanes, the coefficient estimate on the triple interaction is 47bp.

In Column 3, we measure financial stability through credit ratings. The indicator *non–investment grade* takes the value of 1 for firms rated below investment grade (BBB). The coefficient on the interaction term *Indirect hurricane* × *recent hurricane* × *noninvestment grade* is 46 bp. 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.[11]

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

## 4.4 More severe disasters are associated with stronger market reactions

If climate change affects both the frequency and severity of disasters, then market participants should react more strongly to more sizeable disasters for two reasons. First, more severe disasters are more easily observed, and hence priced. Since we estimate the effect of disasters on indirectly affected borrowers, lenders might potentially fail to update their risk assessments, since they fail to observe smaller disasters.

The second channel linking disaster size to the climate change disaster risk premium in lending is that larger disasters cause lenders to update more strongly about the trend in disaster magnitude. Since climate change disaster damage has both a random component and an increasing time trend, lenders can more easily infer a trend in increasing disaster strength for large disasters, while they might assign damage to random fluctuations for smaller disasters.

Ultimately, we cannot differentiate between these two explanations, but either one predicts that major disasters should be associated with more significant pricing effects.

We test this conjecture in Table 6. In our main analysis, we consider hurricanes that caused cumulative damage in excess of $100 million to define our measure of disaster exposure. In the following tests, we analyze whether more severe disasters are associated with more significant market reactions.[12] Specifically, we focus on the

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

[12]In Appendix Table A.8, we calculate our measure of exposure for cutoffs of $50 million, $100 million and $200 million for our pooled sample of climate change related disasters. As in the case of hurricanes alone, larger disasters are associated with stronger increases in credit spreads.

distinction between regular hurricanes and three super storms with particularly wide ranging damages exceeding $100bn, hurricane Katrina, hurricane Maria, and hurricane Harvey. Table 6 presents the results.

[Table 6 here]

The results show that normal hurricanes are associated with rate increases of about 16 basis points, similar to our main results. Column 2 shows that the large hurricanes are associated with rate increases that are about twice as big (31 bp), and these results stay unchanged when we estimate them jointly in column 3. Both hurricanes Katrina and Harvey were the most devastating hurricanes recorded at their time, meaning they provided particularly stark data points for lender to update their risk assessments. Consistent with this interpretation, lenders increased spreads for at-risk borrowers particularly strongly after those storms.

## 4.5 How is climate change risk priced in the secondary market?

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

To investigate how selection in the primary loan markets affects our results, we turn to the pricing of loans in the *secondary* loan market. Since these are prices for already outstanding loans, there are no selection concerns. We obtain secondary market loan prices from Refinitiv's Loan Pricing Corporation. The secondary market data consist of self-reported information from brokers who quote daily prices on loans. The volume of trading in the secondary market has increased substantially in recent years (Beyhaghi and Ehsani, 2017), and we can obtain pricing information for 1,737 loans from 2001 to 2018.

The secondary loan market is generally illiquid. While brokers quote daily prices, there is no information on whether trades actually occurred. To avoid drawing inferences from stale prices, we aggregate quotes for each loan at the weekly level. Then, in an event study setting, we test the price reaction of these loans for firms that suffer an indirect impact of a natural disaster.

[Table 7 here]

In Table 7, the outcome variable is the logarithmic of each existing loan's weekly average quote price. In Column 2, we add loan fixed effects, which capture the average discount at which a loan is trading relative to par. In column 3, we control for year fixed effects to capture time variation in secondary loan prices. Finally, in column 4, our regressions control for both observable and unobservable loan characteristics through loan fixed effects as well as time effects through year fixed effects. To ensure our results are not driven by within-loan time trends in prices, we cluster standard errors at the loan level.

The results in Table 7 confirm our findings from the study of loan spreads at origination. The secondary market loan prices of at-risk, but unaffected borrowers drops by between two and three percent after a hurricane.

These results show that investors in the secondary market price climate change risk through increasingly severe natural disasters. The economic magnitude of these estimates is significantly larger than the estimates of the primary loan market. A back-of-the-envelope calculation that links changes in yield to changes in price suggests that an increase in annual yield of about 18 bp, taken at median loan maturity of about five years, translates to a naive change in loan price of about one percentage point. The estimates from the secondary market are about two times as large. This finding suggests that there is selection in the primary loan market, since the most severely affected borrowers do not originate new loans shortly after a disaster, either voluntarily or because they are excluded from the market. Consistent with this interpretation, in unreported results, we find a substantial drop in liquidity in the secondary loan market following climate change disasters, with bid–ask spreads widening substantially above their normal level.[13] Jointly, these findings from the secondary loan market

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

not only provide an independent verification of our primary loan market results but also hint at the effect of climate change disasters on loan *access*, which goes beyond our main results on loan *pricing*.

## 4.6 Attention to climate change drives banks' lending decisions

Banks' ability to correctly price climate change risk depends on their ability to observe it, and there is wide evidence that investor attention is limited and can be focused by major events.

Therefore, we test for time variation in banks' pricing of climate change–induced lending risk. Specifically, we use the Wall Street Journal index introduced in Engle et al. (2021) to measure time varying attention to climate change.[14] We present these cross-sectional tests in Table 8:

[Table 8 here]

These tests are similar to those in our main specification, except for the addition of triple interactions of $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$, with various measure of climate change attention. We expect the coefficient on these interaction terms to be positive if banks pay more attention to climate change following these reports and adjust their interest rates more substantially for borrowers with exposure to climate change disasters.

In Column 1 of Table 8, we find that the estimated coefficient on the triple interaction $Indirect\ hurricane_{i,t} \times recent\ hurricane_t \times WSJ\ index$, where $WSJ\ index$ is the standardized version of the index in Engle et al. (2021), indeed is positive at 41.7 bp 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 bp. This result suggests that banks indeed 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.

Previous studies find that both equity investors (Choi, Gao, and Jiang, 2020; Alok, Kumar, and Wermers, 2020) and corporate managers (Dessaint and Matray, 2017) can overreact to salient impressions of climate change

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

and extreme weather. Our findings imply that lenders might be subject to similar recency bias when pricing climate change risk.

To further investigate whether attention to climate change disasters is time varying, we directly estimate the development of loan spreads relative to an (indirect) climate change disaster shock. Table 9 presents the results of dynamically estimating our main model.

[Table 9 here]

The coefficient of interest is $Indirect\ hurricane \times recent\ hurricane\ (t\ quarters\ prior)$, which is the interaction of two indicators: one indicator that takes the value of 1 for firms that were classified as having a high exposure to hurricanes and another indicator for the recent occurrence of a hurricane $t$ quarters before the loan was issued. Analogously, $recent\ hurricane\ (t\ quarters\ future)$ is an indicator for loans taken out $t$ quarters before a hurricane strikes.

The results in Table 9 are consistent with time-varying, transient attention to climate change: The coefficient estimate is positive and statistically significant for the quarter in which the hurricane strikes and also for the subsequent four quarters, but this effect vanishes quickly. These findings are consistent with salient information processing by lenders, similar to CEOs overreacting to direct impacts of natural disasters (Dessaint and Matray, 2017).

While these findings are consistent with salience, we cannot fully rule out another interpretation. Borrowers who are at risk of hurricanes and who observe the increasing severity of those hurricanes might actively relocate their operations out of harm's way, similar to the behavior observed in international supply chains (Pankratz and Schiller, 2019). If such a relocation is fast, it could partly explain the transient nature of our findings.

## 4.7 Alternative economic explanations

Our results, which show that banks adjust their loan spreads for borrowers exposed to climate change disasters, could be driven by an internal-funding channel in which banks ration credit and increase loan spreads to borrowers in unaffected areas to supply credit to directly affected borrowers (Cortés and Strahan, 2017). While our $Bank \times year$ fixed effects in the main specification absorb these contemporaneous shocks, we conduct an exercise in Table

10 in which we explicitly control for banks' disaster exposure. Table 10 repeats our primary specification with both the pure fixed effects setting (Columns 1 and 3) as well as the complete specification (Columns 2 and 4).

[Table 10 here]

In addition, these regressions control for the lending bank's exposure to disasters both in the form of the total number of affected loans from this lender (Columns 1 and 2) and the total amount of these loans (Columns 3 and 4). We find that our estimate for $\textit{Indirect hurricane}_{i,t} \times \textit{recent hurricane}_t$ remains economically and statistically almost unchanged from the estimates in Table 2, at around 14 to 18 bp. The estimate for our measures of bank exposure are about +3 bp, and they are statistically significant in Columns 1 and 3. Therefore, while some evidence shows that banks increase interest rates after natural disasters, our results suggest that this increase does not drive the increased spread for borrowers who are *indirectly* exposed to climate change disasters.

Another potential channel for our results could be that they reflect disaster spillovers across supply chains (Barrot and Sauvagnat, 2016). Table 11 tests this conjecture using data from (Barrot and Sauvagnat, 2016) on specific customer–supplier links to quantify the degree to which borrowers are affected by disasters through their supply chains. As before, odd (even) columns present estimates from the fixed effects only (most complete) specifications.

[Table 11 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, our main coefficient estimate $\textit{Indirect hurricane}_{i,t} \times \textit{recent hurricane}_t$ remains between 14 and 17 bp. We, therefore, find that exposure to disaster (for both customers and suppliers) does not affect loan spreads 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 potential alternative channel explaining our results could be the seasonality of hurricanes. Since earthquakes do not follow a seasonal patterns, one might think that borrowers that issue a loan during hurricane season face a risk premium since lenders do not know if a hurricane might strike the borrower soon after. To rule out this alternative explanation, in Appendix Table A.12 we explicitly exclude all loans made during hurricane season, i.e. June through November each year. We find that our estimated coefficient on *indirect hurricane* × *recent hurricane* is, if anything, amplified by this restriction. This robustness is expected, since our definition of *recent hurricane* as a lagged 3 month window means that many treated loans are actually made *after* the hurricane season is over.[15]

### 4.8 Does climate change risk have real effects?

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

[Table 13 here]

We hypothesize that those firms that are most dependent on bank financing will react most severely to an indirect climate change disaster impact. As before, we identify these firms by their lack of an investment-grade credit rating. These firms also experience the largest increase in financing costs, as shown in Table 5.

Our results are consistent with climate change disasters having real effects on firms. In Column 1 of Table 13, we saturate our model with only firm fixed effects. After an indirect hurricane strike, firms reduce their relative investment by about 0.39% compared to the same firm's investment in other years. This is an economically sizeable effect of about 7% compared to the unconditional mean. In Column 2, we add time fixed effects to account for time-varying capital supply conditions, and in Column 3, we add additional firm controls for size, profitability, and leverage. We find that firms with less access to public capital markets due to the absence of an investment-grade credit rating reduce their investment by about 0.28% after an indirect climate disaster impact, and this finding remains robust in all these specifications, although it is statistically insignificant at conventional levels in column 3. Compared to the unconditional sample mean investment rate of 2.15%, our coefficient estimates imply an economically sizeable reduction in investments by almost 10%.

[15] In addition, seasonality is unlikely to drive our result since most loans have a maturity of multiple years, meaning that all loans include multiple hurricane seasons during their life time. Seasonality of issuing also would not explain our secondary market results, and finally, our placebo test on winter weather in Appendix Table A.5 should be affected by seasonality as much as hurricanes.

Finally, in Columns 4 to 6, we investigate whether lower investment by especially affected firms is accompanied by higher precautionary cash holdings. If indirectly affected borrowers fear worsening access and pricing of credit in the future, they should increase their cushion of cash to service their liabilities. Consistent with this idea, we find that firms increase their cash reserves by about 4% after an indirect climate change disaster impact, although this effect is only present particularly vulnerable, non investment grade, borrowers. This estimate represents an economically large relative increase of 9% compared to the unconditional sample mean of 45%. These results show that both lenders and firms react to an indirect climate change disaster impact. Indirectly affected firms reduce their investment and increase their cash reserves, which is consistent with updated expectations regarding the increased frequency and severity of future climate change disasters.

### 4.9 Additional tests

We perform a series of additional tests with respect to the data definitions shown in Appendix A.2.

One concern could be that our sample period feature no major earthquakes in the U.S., and this relative absence of major shocks explains our finding in Table 3, rather than the fact that banks do not update about the frequency and severity of non-climate change related disasters. To rule this explanation out, we conduct a robustness exercise in Appendix Table A.2 in which we define *recent eartquake abroad* using the 13 largest global earthquakes gloabally since the year 1996. These disasters include some of the most destructive high profile events including the 2004 Sumatra earthquake causing the Boxing Day Tsunamis with more than 200,000 fatalities, the 2011 Tohoku earthquake that caused the nuclear emergency in Fukushima, and the 2010 Haiti earthquake with more than 150,000 fatalities. If our non-results in Table 3 are due to the small size of events in the U.S., these major earthquakes should elicit a pricing reaction. However, the results in Appendix Table A.2 are economically small and statistically insignificant in all specifications. This result supports our interpretation that the increased spreads following climate change related disasters reflect updating of lenders on the frequency and severity of disasters due to climate change, whereas non-climate change related disasters do not elicit updating.

We repeat our main analysis separately for each climate change disaster and non–climate change disaster separately. Following the IPCC, we classify floods and wildfires as disasters that have increased in severity due to climate change. Appendix Tables A.3 and A.4 show that our results are robust in these individual regressions.

The coefficient estimates on $Indirect\ flood_{i,t} \times recent\ flood_t$ is about 9 bp across the various specifications. The coefficient estimate on $Indirect\ fire_{i,t} \times recent\ fire_t$ is very similar at about 8.5 bp on average. Both of these estimates are positive and comparable to the coefficient estimate for hurricanes in our main Table 2, and their smaller absolute size likely reflects the relatively lower damages caused by these disasters compared to hurricanes.

Similarly, we consider severe winter weather as non-climate change related disasters, in accordance with the IPCC. The coefficient estimate on $Indirect\ winter\ weather_{i,t} \times recent\ winter\ weather_t$ in Appendix Table A.5 is negative and is both economically and statistically insignificant, just like the coefficient estimate on earthquakes in Table 3.

As an alternative to individually estimate the effects of climate change disasters and non–climate change disasters, we can pool the three disasters in each group. Table A.6 reports the coefficient estimates obtained from this process for hurricanes, wild fires, and floods. The coefficient estimate on $Indirectdisasters \times recentdisasters$ ranges from 6 to 8 bp, which is slightly smaller than the estimates from the individual disaster regressions.

In a similar analysis, Table A.7 shows that pooling earthquakes and winter weather yields a coefficient estimate that is statistically insignificant (although small and positive). These results hold when we jointly estimate coefficients on the two groups in Table 4.

While hurricanes are major natural disasters, most of the other disasters can often cause less damage. This difference allows us to estimate the differential effect of disaster size on loan pricing reactions with more granularity than in Table 6. In Table A.8, we estimate the effect of $Indirectdisasters \times recentdisasters$ for disasters that inflict a minimum of \$50 million, \$100 million, and \$200 million in damage, respectively. We find that the coefficient estimates increase monotonically with disaster size: 3 bp for disasters with \$50 million in damages, 6 bp for \$100 million disasters, and 9 bp for \$200 million disasters.

We also implement a set of additional sample selection robustness tests in Appendix A.2.

We first show that our results are not driven by the cyclicality of hurricane seasons by including Bank $\times$ hurricane-season fixed effects, nor by specific business cycles in industries operating in hurricane prone areas by including industry $\times$ year-quarter FE. Both of these tests, displayed in Appendix Table A.9 yield coefficient estimates that are economically and statistically stronger than those in our main specification.

In Appendix Table A.10, we use an alternative proxy for market attention to climate change, namely the recent publication of IPCC reports. These reports, that are published about once very seven years. Our sample features three reports in 2001, 2007, and 2014. We define periods of high attention as the two years following each major report and estimate a triple interaction between an indicator for these years and our main specification.[16] We find that loan spreads spike substantially more after a hurricane for indirectly affected borrowers during those years of high attention, with the coefficient estimate on the triple interaction ranging from 87 to 96 basis points, about 5 times our main, un-interacted coefficient in these specifications which remains similar to the main test.

We then modify our measure of firms' geographic footprint by focusing on employment, rather than business locations. When we re-estimate our main test using this modify exposure measure in Appendix Table A.11, the coefficient estimate on Indirect hurricane (employment) × recent hurricane is comparable, though economically slightly smaller than in our main specification, at 13 to 15 basis points.

We then show out that our results are not driven by the credit market freeze during the financial crisis. We drop all observations from July 2007 until July 2009 in Appendix Table A.13, and our results remain economically and statistically very similar to the main specification.

In Appendix Table A.14 we re-estimate our main specification with different definitions of hurricane exposure. In column 1, we sort firms into quintiles based on the general sample of firms each year, rather than the sample of firms issuing loans in a given year. In column 2, we replace the indicator for the highest quintile of this measure with its continuous version. In column 3, we do the same continuous estimation for our main measure of indirect exposure (quintiles based on firms issuing loans each year), and in column 4, we replace the top quintile measure with an indicator for any hurricane exposure at all (which effectively is an above-median indicator since about half of our firms have zero hurricane exposure). Our results are economically and statistically very similar to our main specification in each of these tests.

One remaining concern could be that earthquakes are rare in the US during our sample and the rolling ten year classification for at-risk counties might not truly capture earthquake exposure. In Appendix Tables A.15 we re-estimate our earthquake test with an infinite window. We find that the triple interaction between recent hurricanes and indirect hurricane exposure measured in this way is statistically insignificant as in Table 3, and economically actually sizeable and negative.

[16] No major hurricanes occured during the 12 months after each report.

# 5 Conclusion

We investigate a channel through which climate change affects businesses, the link between bank lending and natural disasters related to climate change. To overcome the simultaneity challenge when comparing direct disaster damage to updates in banks' expectations about future disasters, we estimate reactions in loan spreads for borrowers that are at risk but not directly affected by disasters. The rates that banks charge these indirectly affected borrowers increase by about 18 basis points (bp) , or 11% compared to the unconditional loan spread.

These effects are strongest for borrowers who are least able to internalize a potential adverse shock, and the effects are more pronounced for more severe disasters. Consistent with time-varying attention to climate change, this effect is concentrated in periods of high public attention to climate change, but short-lived.

Our findings provide the first evidence that climate change currently affects lending conditions for borrowers in the corporate lending market through the increasing severity of natural disasters. Many questions remain for future research. First and foremost is the question of whether firms and banks may shift their operations away from regions affected by climate change–related disasters to mitigate the potential medium and long term effects of climate change.

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# Figures

Figure 1: Direct exposure to climate change related disasters over time
The figure presents the effect of direct exposure to climate change related disasters over time. Climate change related disasters are defined as hurricanes, wildfires and floods. Direct treatment is defined as firms being in the top 20% of firms based on operations-weighted exposure to counties with direct hits by climate change related disasters. Vertical lines represent 90% confidence intervals clustered by borrower and year. The years 1996 to 2001 form the base period.

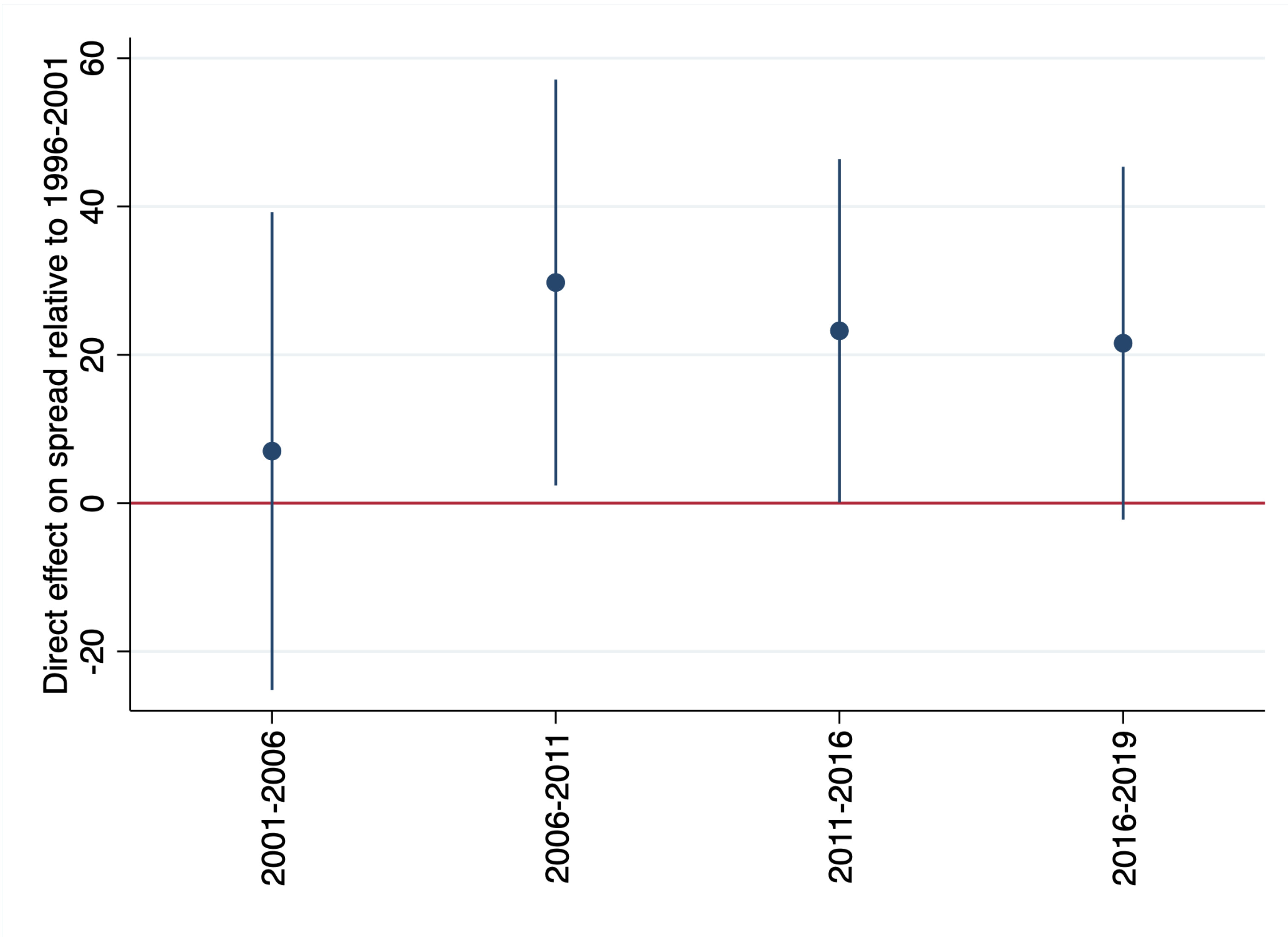


Figure 2: Geographic hurricane exposure 1996

The figure presents county level hurricane exposure in 1996 based on the number of previous hits.

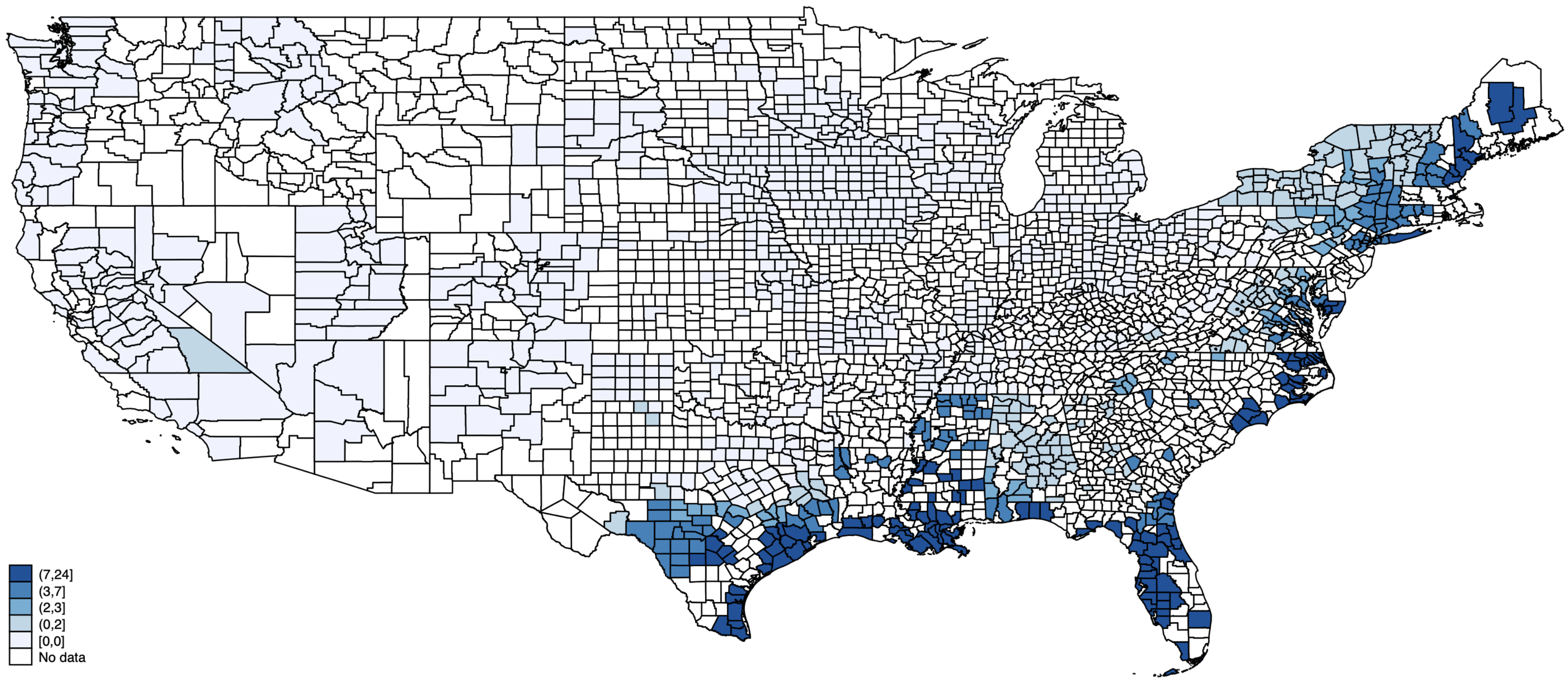
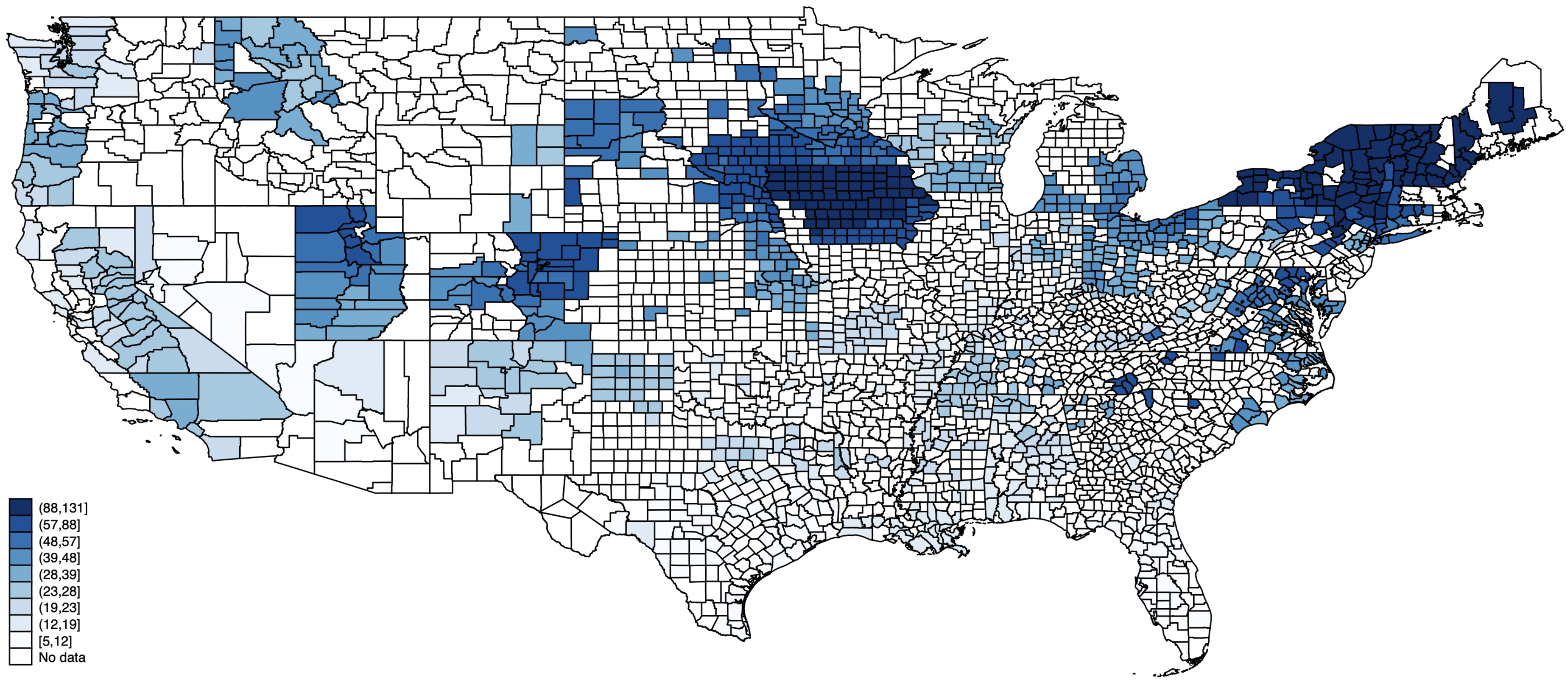


Figure 3: Geographic winter weather exposure 1996
The figure presents county level hurricane exposure in 1996 based on the number of previous hits.



# Tables

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

Panel A: Loan characteristics and disaster variables

| | N | Mean | Std Dev | 25th | Median | 75th |
|---|---|---|---|---|---|---|
| Spread (bp) | 21262 | 170.46 | 120.75 | 75.83 | 150.00 | 228.83 |
| Maturity (year) | 21262 | 3.98 | 1.85 | 2.92 | 5.00 | 5.00 |
| Loan amount ($ million) | 21262 | 1405.81 | 2019.76 | 261.60 | 649.73 | 1597.81 |
| Financial covenant (dummy) | 21262 | 0.58 | 0.49 | 0.00 | 1.00 | 1.00 |
| Number of financial covenant | 21262 | 1.25 | 1.31 | 0.00 | 1.00 | 2.00 |
| Term loan | 21262 | 0.22 | 0.36 | 0.00 | 0.00 | 0.42 |
| Revolving loan | 21262 | 0.74 | 0.39 | 0.45 | 1.00 | 1.00 |
| Borrower total asset ($ billion) | 21262 | 26.23 | 74.28 | 1.09 | 3.60 | 13.59 |
| Borrower ROA | 21262 | 0.13 | 0.09 | 0.08 | 0.12 | 0.17 |
| Borrower debt to asset | 21262 | 0.35 | 0.22 | 0.20 | 0.33 | 0.48 |
| Indirect hurricane | 21262 | 0.19 | 0.40 | 0.00 | 0.00 | 0.00 |
| Indirect earthquake | 21262 | 0.20 | 0.40 | 0.00 | 0.00 | 0.00 |
| Recent hurricane | 21262 | 0.10 | 0.30 | 0.00 | 0.00 | 0.00 |
| Recent earthquake | 21262 | 0.04 | 0.20 | 0.00 | 0.00 | 0.00 |

Panel B: Disaster Damages

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

Table 2: Interest rate spreads and climate change related disasters

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the proceeding 3 months. 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 3: Rates and non-climate change related disasters

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

| Rates (in bp) non-climate change disasters | | | | |
|---|---|---|---|---|
| | Spread | | | |
| | (1) | (2) | (3) | (4) |
| *Indirect earthquake* × *Recent earthquake* | -4.202 | -3.498 | -1.889 | -1.391 |
| | (7.216) | (7.258) | (6.513) | (6.581) |
| *Indirect earthquake* | -3.358 | -3.440 | -0.260 | -0.336 |
| | (4.675) | (4.615) | (4.415) | (4.389) |
| *Recent earthquake* | 11.868** | 11.541** | 11.593** | 11.373** |
| | (5.526) | (5.522) | (4.832) | (4.877) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.762 | 0.762 | 0.774 | 0.775 |
| Direct Disaster Exposure | Yes | Yes | Yes | Yes |
| Bank × Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan Controls | No | Yes | No | Yes |
| Firm Controls | No | No | Yes | Yes |

Table 4: Climate change and non-climate change disasters jointly

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

| Rates (in bp) climate change and non-climate change disasters | | | | |
|---|---|---|---|---|
| | Spread | | | |
| | (1) | (2) | (3) | (4) |
| *Indirect hurricane* × *Recent hurricane* | 17.306** | 18.814** | 19.146** | 18.733** |
| | (7.874) | (8.516) | (8.753) | (8.616) |
| | (4.310) | (3.962) | (3.820) | (3.781) |
| *Indirect earthquake* × *Recent earthquake* | -2.433 | -3.481 | -1.845 | -1.348 |
| | (7.905) | (7.243) | (6.490) | (6.563) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.736 | 0.762 | 0.775 | 0.775 |
| Bank × Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan Controls | No | Yes | No | Yes |
| Firm Controls | No | No | Yes | Yes |

Table 5: Cross sectional effects on high risk borrowers

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last 3 months. *High leverage* is an indicator equal to 1 for firms with leverage in the fourth quartile. $Non-investment\ grade$ is an indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB). The sample excludes loans to 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

| Rates (in bp) and high risk borrowers | | | |
|---|---|---|---|
| | Spread | | |
| | (1) | (2) | (3) |
| *Indirect hurricane* × *recent hurricane* | 17.538* | 15.877* | 7.114 |
| | (8.888) | (8.003) | (9.292) |
| *Indirect hurricane* × *recent hurricane* × *market leverage* | 25.262* | | |
| | (14.684) | | |
| *Indirect hurricane* × *recent hurricane* × *tangibility* | | 14.477* | |
| | | (8.028) | |
| *Indirect hurricane* × *recent hurricane* × $non-investment\ grade$ | | | 45.984* |
| | | | (23.960) |
| $N$ | 20269 | 20616 | 19658 |
| $R^2$ | 0.746 | 0.741 | 0.753 |
| Bank × Year FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Loan Controls | Yes | Yes | Yes |
| Firm Controls | Yes | Yes | Yes |
| Other interactions | Yes | Yes | Yes |

Table 6: Effects and disaster size

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last 3 months. *Recent hurricane*$_{>\$100bn}$ indicates the hurricanes with a total losses exceeding \$100 billion, *Recent hurricane*$_{>other}$ indicates the rest major hurricanes. 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 7: Climate change risk in the secondary market
This table reports regressions of log of loan weekly average quote price in the secondary market on borrowers' indirect hurricane risk indicator with the occurrence of hurricanes in the last four weeks.. The sample includes existing loans' weekly quotes in 12 weeks before or after a hurricane hit, but excludes loans to the firms that are directly affected by a major hurricane. Parentheses contain standard errors clustered by loan. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 8: Time varying attention to climate change and interest rate spreads

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last 3 months. *WSJ index* is the standardized attention index constructed in Engle et al. (2021) in the month when a loan is issued,lagged by one quarter. *above median attention*, *medium tercile attention*, and *top tecile attention* are indicators for loans issued in months with above median, medium tercile, and highest tercile attention to climate change me assured by the index, lagged by one quarter. 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 9: Are the pricing effects permanent?

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last 3 months. 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively..

| Development of rates (in bp) over time | | | | |
|---|---|---|---|---|
| | Spread | | | |
| | (1) | (2) | (3) | (4) |
| *Indirect hurricane × Future hurricane_4 quarters future* | 0.207 | 1.147 | -2.305 | -1.301 |
| | (5.317) | (5.726) | (4.590) | (5.073) |
| *Indirect hurricane × Future hurricane_3 quarters future* | 2.619 | 3.400 | 2.175 | 2.891 |
| | (9.561) | (9.731) | (8.934) | (9.214) |
| *Indirect hurricane × Future hurricane_2 quarters future* | -0.631 | 0.077 | -0.776 | 0.030 |
| | (9.593) | (8.621) | (8.822) | (8.175) |
| *Indirect hurricane × Future hurricane_1 quarters future* | 6.739 | 5.489 | 5.965 | 4.832 |
| | (7.456) | (7.147) | (7.442) | (7.061) |
| *Indirect hurricane × Recent hurricane_This quarter* | 18.722* | 18.995 | 20.774* | 20.932* |
| | (10.220) | (11.866) | (10.381) | (11.769) |
| *Indirect hurricane × Recent hurricane_1 quarter prior* | -4.692 | -2.476 | -6.379 | -4.123 |
| | (9.731) | (10.000) | (8.688) | (9.100) |
| *Indirect hurricane × Recent hurricane_2 quarter prior* | -8.125 | -6.651 | -6.360 | -5.144 |
| | (8.551) | (9.247) | (8.294) | (8.994) |
| *Indirect hurricane × Recent hurricane_3 quarters prior* | -12.821 | -8.529 | -11.354 | -7.616 |
| | (7.566) | (8.142) | (7.970) | (8.370) |
| *Indirect hurricane × Recent hurricane_4 quarters prior* | -3.752 | -3.394 | -4.559 | -4.423 |
| | (4.301) | (4.549) | (4.948) | (4.887) |
| $N$ | 21262 | 21262 | 21262 | 21262 |
| $R^2$ | 0.696 | 0.730 | 0.713 | 0.742 |
| Bank× Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan controls | No | Yes | No | Yes |
| Firm controls | No | No | Yes | Yes |

Table 10: Bank disaster exposures and interest rate spreads
This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last 3 months. *Bank disaster exposure* is the ratio of a bank's outstanding loans that are assigned to disaster firms, measured either by loan amount or loan incidence. 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 11: Economic links between borrowers and interest rate spreads

This table reports regressions of loan spread (in bp) on borrowers' indirect hurricane exposure indicator with the occurrence of a major hurricane in the last 3 months. *Customer disaster exposure* and *Supplier disaster exposure* are a borrower's exposure through its customers and suppliers to natural disasters, respectively. The sample excludes loans to 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. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table 12: Firm real effects and climate change risk

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

| Investment, cash holdings, and lagged climate change risk | | | | | | |
|---|---|---|---|---|---|---|
| | CapEx/Lagged Asset (%) | | | Cash / Liabilities (%) | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Indirect\ hurricane \times Recent\ hurricane$ | 0.012 | 0.042 | 0.025 | -4.559*** | -3.754* | -3.007* |
| | (0.125) | (0.091) | (0.082) | (1.686) | (1.936) | (1.731) |
| $Indirect\ hurricane \times recent\ hurricane \times non-investment\ grade$ | -0.399** | -0.398** | -0.277 | 4.036** | 4.226** | 4.075* |
| | (0.174) | (0.170) | (0.208) | (1.809) | (1.854) | (2.069) |
| $N$ | 100556 | 100556 | 88253 | 91255 | 91255 | 89103 |
| $R^2$ | 0.435 | 0.470 | 0.532 | 0.591 | 0.593 | 0.649 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Quater FE | No | Yes | Yes | No | Yes | Yes |
| Firm controls | No | No | Yes | No | No | Yes |
| Other interactions | Yes | Yes | Yes | Yes | Yes | Yes |

Table 13: Indirect hits and future severe weather damage

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

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

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

## A.1 Variable Definitions

| | |
|---|---|
| **Loan Variables** | |
| Spread (bp) | The all-in-drawn spread in basis points |
| Loan amount | Loan amount in dollars, adjusted to 2019 values |
| Maturity (Years) | The number of years between loan start and end dates |
| Term loan | Indicator equal to one if the loan type is term loan |
| Revolving loan | Indicator equal to one if the loan type is revolver |
| Financial covenant (dummy) | Indicator equal to one if the loan contract includes covenants |
| Number of financial covenant | The number of covenants in a loan contract |
| **Disaster Variables** | |
| $Indirect\ hurricane_{i,t}$ | Indicator equal to one if firm $i$ is in the top quintile when we rank firms in month $t$ by their location-weighted exposure to hurricanes. The exposure is based on a firm's total footprints in hurricane-prone counties. A hurricane-prone county in month $t$ is the one which, in the past 10 years, exceeds 90% other counties nationwide in terms of disaster losses caused by hurricanes. |
| $Indirect\ earthquake_{i,t}$ | Indicator equal to one if firm $i$ is in the top quintile when we rank firms in month $t$ by their location-weighted exposure to earthquakes. The exposure is based on a firm's total footprints in earthquake-prone counties. A earthquake-prone county in month $t$ is the one which, in the past 10 years, exceeds 90% other counties nationwide in terms of disaster losses caused by earthquakes. |
| $Recent\ hurricane_t$ | A time dummy equal to one if a hurricane hit during the preceding 3 months. |
| $Recent\ earthquake_t$ | A time dummy equal to one if an earthquake hit during the preceding 3 months. |
| **Other Variables** | |
| $High\ leverage_{i,q}$ | Indicator equal to 1 for firm $i$ with quarter $q$'s leverage ratio in the top quartile. |

| | |
|---|---|
| $Non-investment\ grade$ | Indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB) in S&P rating. |
| $WSJindex$ | The Wall Street Journal climate change news index, a standardized attention index constructed in Engle et al. (2021). |
| $Bank\ disaster\ exposure_{m,t}$ | Bank $m$'s exposure to natural disasters that occur during the preceding 3 months. It is the ratio of the bank's outstanding loans, when a disaster occurs, that are assigned to disaster firms, measured either by loan amount or loan incidence. |
| $Customer\ disaster\ exposure_{i,t}$ | Firm $i$'s exposure through customers to natural disasters that occur during the preceding 3 months. It is the ratio of sales to disaster customers to the firm's total sales in the same quarter. |
| $Supplier\ disaster\ exposure_{i,t}$ | Firm $i$'s exposure through suppliers to natural disasters that occur during the preceding 3 months. It is the ratio of the sales from disaster suppliers to those suppliers' total sales in the same quarter. |

## A.2 Anecdotal evidence

This section provides anecdotal evidence that the link between climate change, natural disasters and credit risk is well understood for financial market participants and impacts bank's lending decisions.

As a first overview, we collect evidence from the 2019 10-K filings of 10 major U.S. banks (by assets). We present an overview of this analysis in Appendix Table A.1. As a first pass, we report whether the 10-K explicitly mentions climate change and natural disasters (or severe weather) in close proximity. Out of the ten banks, all but Morgan Stanley explicitly mention these two topics. Next, we look for any mentioning of a link between increasing severity and frequency of these disasters and climate change. Out of the 9 banks that remain, all but Wells Fargo explicitly state that there is a potential link between climate change and worsening severe weather incidents. In the last column of Appendix Table A.1 we report specific natural disasters mentioned in the context of climate change. Four banks mention specific disasters, with all of them mentioning hurricanes and/or storms. In addition, both Bank of America and JP Morgan Chase reference the risk of wild fires, and JP Morgan Chase mentions floods.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Quotes from United States Fourth National Climate Assessment:

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

On an intnernational 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.**"

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

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

Table A.2: Robustness: Foreign earthquakes and rates

This table reports regressions of loan spread (in basis points) on borrowers' indirect earthquake indicator with the occurrence of one of the ten most serious global earthquakes since 2000, as well as three major earthquakes from 1996 to 2000. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

| | Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Indirect earthquake* × *Recent earthquake abroad* | 3.951 | 3.674 | 2.464 | 2.338 |
| | (6.059) | (6.021) | (5.976) | (5.933) |
| *Indirect earthquake* | -4.562 | -4.540 | -0.950 | -0.972 |
| | (5.691) | (5.626) | (5.274) | (5.228) |
| *Recent earthquake abroad* | 9.989 | 9.988 | 7.983 | 7.988 |
| | (7.063) | (6.974) | (6.997) | (6.953) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.762 | 0.762 | 0.774 | 0.775 |
| Bank×$Year\ FE$ | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan controls | No | Yes | No | Yes |
| Firm controls | No | No | Yes | Yes |

Table A.3: Floods and rates

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

| | Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Indirect flooding* × *Recent flooding* | 9.820* | 9.649* | 8.984* | 8.848* |
| | (4.820) | (4.741) | (4.437) | (4.358) |
| *Indirect flooding* | -2.562 | -2.490 | -1.973 | -1.927 |
| | (4.043) | (3.995) | (3.702) | (3.676) |
| *Recent flooding* | -6.794** | -6.895** | -5.929** | -5.994** |
| | (2.634) | (2.640) | (2.633) | (2.655) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.762 | 0.762 | 0.774 | 0.775 |
| Direct Disaster Exposure | Yes | Yes | Yes | Yes |
| Bank × Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan Controls | No | Yes | No | Yes |
| Firm Controls | No | No | Yes | Yes |

Table A.4: Fires and rates

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

| | Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Indirect\ fire \times Recent\ fire$ | 9.701** | 9.668** | 7.635* | 7.632* |
| | (4.081) | (4.006) | (4.019) | (3.961) |
| $Indirect\ fire$ | -3.789 | -3.900 | -1.489 | -1.572 |
| | (2.689) | (2.654) | (2.568) | (2.560) |
| $Recent\ fire$ | -7.003* | -6.908 | -5.254 | -5.200 |
| | (4.038) | (4.042) | (4.081) | (4.092) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.762 | 0.762 | 0.774 | 0.774 |
| Direct Disaster Exposure | Yes | Yes | Yes | Yes |
| Bank × Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan Controls | No | Yes | No | Yes |
| Firm Controls | No | No | Yes | Yes |

Table A.5: Winter weather and rates
This table reports regressions of loan spread (in basis points) on borrowers' indirect non-climate change related disaster indicator with the occurrence of the same type of disasters. Non-climate change related disasters include winter weather. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

| | | | | |
|---|---|---|---|---|
| *Indirect winter weather* $\times$ *Recent winter weather* | -5.295 | -5.346 | -2.941 | -2.977 |
| | (9.342) | (9.331) | (8.322) | (8.305) |
| *Indirect winter weather* | 9.573*** | 9.611*** | 9.188*** | 9.195*** |
| | (3.083) | (3.039) | (2.757) | (2.761) |
| *Recent winter weather* | 9.840* | 9.804* | 8.264 | 8.248 |
| | (5.747) | (5.677) | (5.655) | (5.609) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.762 | 0.762 | 0.775 | 0.775 |
| Direct Disaster Exposure | Yes | Yes | Yes | Yes |
| 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 A.6: Climate disasters and rates (climate aggregated)
This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster indicator with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties attacked by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

| | Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Indirect disasters* × *Recent disasters* | 8.109*** | 6.460** | 7.308** | 6.045** |
| | (2.664) | (2.493) | (2.689) | (2.557) |
| *Indirect disasters* | -4.756* | -2.906 | -4.282* | -2.683 |
| | (2.643) | (2.374) | (2.448) | (2.224) |
| *Recent disasters* | -0.164 | -0.666 | -0.980 | -1.439 |
| | (3.402) | (3.357) | (3.267) | (3.237) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.735 | 0.762 | 0.753 | 0.775 |
| Direct Disaster Exposure | Yes | Yes | Yes | Yes |
| Bank × Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan Controls | No | Yes | No | Yes |
| Firm Controls | No | No | Yes | Yes |

Table A.7: Non-climate disasters and rates (non-climate aggregated)
This table reports regressions of loan spread (in basis points) on borrowers' indirect non-climate change related disaster indicator with the occurrence of the same type of disasters. Non-climate change related disasters include tornadoes, winter weather, and earthquakes. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties attacked by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

| | Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Indirect disasters* × *Recent disasters* | 4.224 | 3.234 | 5.537 | 4.415 |
| | (3.427) | (3.765) | (3.559) | (3.787) |
| *Indirect disasters* | 2.844 | 4.319 | 4.332 | 5.504 |
| | (4.023) | (3.729) | (3.667) | (3.489) |
| *Recent disasters* | 2.360 | 1.706 | 0.976 | 0.604 |
| | (4.114) | (3.807) | (4.021) | (3.783) |
| $N$ | 21127 | 21127 | 21127 | 21127 |
| $R^2$ | 0.735 | 0.762 | 0.753 | 0.775 |
| Direct Disaster Exposure | Yes | Yes | Yes | Yes |
| Bank × Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan Controls | No | Yes | No | Yes |
| Firm Controls | No | No | Yes | Yes |

Table A.8: Effects and disaster size (climate aggregated)
This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster indicator with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table A.9: Robustness: seasonality and industry controls

This table reports regressions of loan spread on borrowers' indirect natural disaster indicators with the occurrence of the same type of disasters. Both climate and non-climate change related disasters are included, defined as hurricanes and earthquakes, respectively. The sample excludes loans to the firms that are directly affected by those disasters. 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 and non-earthquake disasters if any. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table A.10: Time varying attention to climate change and rates - IPCC reports

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

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

Table A.11: Climate disasters and rates (employment weighted operations)
This table reports regressions of loan spread (in basis points) on borrowers' indirect climate change related disaster indicator with the occurrence of major hurricanes. We calculate firms' exposure to climate hurricane prone areas using employment weights, rather than operations weights. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

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

Table A.12: Robustness: Exclude hurricane season

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

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

Table A.13: Robustness: Main test excluding financial crisis

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

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

Table A.14: Robustness: Rates and climate change related disasters - continuous treatment

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

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

Table A.15: Robustness: Rates and non-climate change related disasters - no 10 year window
This table reports regressions of loan spread on borrowers' indirect earthquake exposure indicator with the occurrence of a major earthquake in the last 3 months. Unlike in the main specification, where we measure earthquake exposure using a 10 year rolling window, we utilize the complete disaster history to measure earthquake exposure in these tests. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

| Rates (in bp) non-climate change disasters | | | | |
|---|---|---|---|---|
| | Spread | | | |
| | (1) | (2) | (3) | (4) |
| *Indirect earthquake* × *Recent earthquake* | -18.220 | -14.966 | -18.072 | -18.363 |
| | (13.774) | (11.169) | (10.617) | (16.032) |
| *Indirect earthquake* | -4.635 | -5.319 | -3.894 | -3.835 |
| | (4.602) | (4.345) | (4.200) | (4.003) |
| *Recent earthquake* | 10.470 | 9.034 | 9.514 | 9.473 |
| | (11.371) | (8.733) | (8.025) | (6.272) |
| $N$ | 24042 | 24042 | 24042 | 24042 |
| $R^2$ | 0.686 | 0.722 | 0.734 | 0.735 |
| Bank× Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Loan controls | No | Yes | No | Yes |
| Firm controls | No | No | Yes | Yes |