# When Disasters Strike: Climate Risk, Bank Lending Dynamics and The Spillover Effects

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## Abstract

This thesis investigates how banks adjust their lending dynamics to U.S. firms in response to climate-related disasters, focusing on post-disaster credit reallocation and portfolio rebalancing. Using syndicated loans from DealScan and disaster loss data from SHELDUS, the study analyzes banks' strategic shifts in credit supply and pricing mechanisms following extreme weather events. The findings reveal that banks reduce credit supply at the extensive margin while increasing loan pricing (spreads) in disaster-affected regions. At the intensive margin, loan-level analysis shows that banks initially raise interest rates for affected borrowers but later reduce them and expand credit as economic conditions stabilize. This suggests that banks prioritize pricing mechanisms before adjusting non-pricing loan terms when issuing new contracts. Following natural disasters, banks reallocate capital by shifting credit away from high-risk areas to neighboring states, which serve as financial buffers by absorbing increased credit demand while mitigating risk exposure. However, at the contractual level, this effect is absorbed. In unaffected states, a persistent decline in credit supply at both the state and loan levels reinforces the robustness of these findings and highlights the systematic nature of credit reallocation. Banks strategically redirect resources toward higher-demand regions while preserving liquidity through shorter maturities. Additionally, banks exhibit selection bias, initially raising borrowing costs for large, high-quality and profitable firms to subsidize lower rates for riskier borrowers. Over time, this strategy reverses, as banks lower spreads for financially stronger firms and expand credit to businesses that demonstrate resilience post-disaster.


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## Resumo

Esta tese analisa como os bancos ajustam a concessão de crédito a empresas nos Estados Unidos em resposta a desastres climáticos, com foco na realocação de crédito pós-desastre e no reequilíbrio das carteiras. Utilizando dados de empréstimos do DealScan e perdas associadas a desastres do SHELDUS, o estudo investiga as mudanças estratégicas na oferta de crédito e na fixação de preços adotadas pelos bancos após eventos climáticos extremos. Os resultados indicam que os bancos reduzem a oferta de crédito na margem extensiva, aumentando simultaneamente os spreads nas regiões afetadas. Na margem intensiva, a análise demonstra que, inicialmente, as instituições financeiras aumentam as taxas de juro para os mutuários afetados, mas posteriormente reduzem-nas e expandem a concessão de crédito à medida que as condições económicas estabilizam. Isto sugere que os bancos priorizam mecanismos de fixação de preços antes de ajustarem os termos contratuais. Após desastres naturais, os bancos realocam capital ao transferir crédito de áreas de alto risco para estados vizinhos, funcionando como buffers financeiros, que absorvem a procura adicional e mitigam o risco. No entanto, a nível contratual, este efeito é absorvido. Nos estados não afetados, a contração persistente da oferta de crédito confirma a sistematicidade da realocação. Além disso, os bancos inicialmente aumentam os custos de financiamento para empresas grandes e lucrativas para subsidiar taxas mais baixas a empresas de maior risco. Com o tempo, esta estratégia inverte-se, reduzindo-se os spreads para empresas mais sólidas e expandindo-se o crédito para aquelas que demonstram resiliência no período pós-desastre.

*Título: "When Disasters Strike: O Impacto das Catástrofes Naturais na Dinâmica dos Empréstimos Bancários e os Efeitos de Contágio"*

*Autor: Maria Isabel Ferreira*

*Palavras-chave: Exposição ao Clima, Efeito de Decomposição, Dinâmica de Concessão e Crédito, Realocação de Crédito, Efeitos de Spillover, Enviesamento de Sobrevivência*

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# LIST OF ABBREVIATIONS

**FE** Fixed Effects

**FEMA** Federal Emergency Management Agency

**GDP** Gross Domestic Product

**ROA** Return on Assets

**SBA** Small Business Administration

**SHELDUS** Spatial Hazard Events and Losses Database for the United States

# GLOSSARY

**Altman's Z-score** is the sum of 3.3 times pre-tax income, sales, 1.4 times retained earnings, and 1.2 times net working capital all divided by total assets

**Book-to-market** is the ratio of the market value of assets to total assets, where the numerator is defined as the sum of market equity, total debt and preferred stock liquidation value less deferred taxes and investment tax credits

**Leverage** is the ratio of total debt from the balance sheet to total assets

**Return on Assets** is the ratio of net income to total assets

# 1. Introduction

Climate risk has gained significant importance in the financial sector, compelling both investors and financial institutions to reevaluate their risk management frameworks and lending practices. The rising frequency and severity of extreme natural disasters due to climate change have material effects on the economy and the banking sector.

Climate risk can be broadly classified into three distinct categories: physical risk, regulatory risk and transition risk. Growing concerns about the risks posed by climate change underscore the need to understand how banks adjust their lending practices to navigate these evolving challenges. If financial institutions accurately account for physical risk, banks are likely to either adjust their strategies or gradually withdraw from high-risk geographical areas (Meizenzhal, 2023). However, post-disaster regions often face increased credit demand, forcing financial institutions to reallocate resources to support recovery efforts (Cortés, 2017). Banks have proven to be efficient in facilitating the recovery of local economies (Cortés, 2014; Celil, 2022). Beyond transaction volumes, it is crucial to examine the pricing mechanisms banks employ, as mispricing could undermine financial stability. Additionally, non-pricing tools play a vital role in enhancing banks' ability to monitor and adapt their lending practices, thereby providing greater flexibility in managing risk (Boot, 1991).

This study addresses several critical questions: Whether and how do banks adjust their lending practices in response to the materialization of climate-related disasters. Does the impact extend to neighboring regions, influencing credit allocation decisions? And what about unaffected regions? Do banks employ a screening mechanism in post-disaster lending? To answer these questions, this research examines whether banks adjust both pricing and non-pricing terms to manage climate exposure, including loan spreads, amounts, term-to-maturity, covenants and collateral requirements.

I address these questions using multiple data sources. First, I retrieved data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to compute climate exposure, defined as the aggregated disaster-related damage across states (Javadi and Masum, 2021). This climate exposure measure is further scaled against each state's GDP to capture the relative impact of disaster damage in proportion to a state's economic wealth. This adjustment accounts for the fact that wealthier states may experience less severe economic disruptions compared to those with lower economic resilience. The climate data is subsequently matched with firm-level syndicated loan data from DealScan for the period 2000-2023, using the state location of each firm's headquarters.

The findings are twofold: at the aggregate (state) level, there is a contraction in credit supply subsequent to severe climate disasters and an increase in borrowing costs. However, at the loan level, after controlling for firm and loan characteristics, I find that banks do not immediately adjust non-pricing loan mechanisms post-disaster. Instead, interest rates rise sharply. Over time, as economic conditions stabilize and insurance interventions take effect, banks gradually lower interest rates and expand credit supply, favoring firms that demonstrate resilience or benefit from institutional support. The findings of this study highlight two key mechanisms: 1) the over-time diffusions of the post-disaster shock via various lending conditions and 2) the screening of firms that successfully "survived" the post-disaster shock period. The former refer to the gradual reduction of immediate disaster impacts over time, while the latter describes how banks identify and support firms that have demonstrated resilience. In the short run, banks primarily rely on pricing mechanisms to mitigate post-disaster risk, particularly for high-quality and highly profitable firms, while subsidizing lower borrowing costs for financially weaker firms to ensure credit access for those most in need. As the recovery unfolds, this strategy shifts - banks reduce spreads for stronger firms and expand credit supply to businesses that have successfully endured the disaster period. Rather than displaying outright risk aversion, banks adopt a strategic approach, balancing financial stability with economic recovery. Both state-level and loan-level analyses are essential to capturing the full picture of post-disaster lending decisions. State-level analysis aggregates data across many firms, providing a broad perspective on lending patterns and capturing the overall reduction in credit supply as banks limit exposure to high-risk areas. In contrast, loan-level analysis focuses on individual firms that remain in the sample, offering detailed insights into how banks adjust specific contractual terms, such as interest rates, loan sizes, and collateral requirements. While this granular approach highlights individual lending decisions, it doesn't reflect the broader trends in credit supply observed at the state-level, as it isolates contract-specific adjustments and omits the macro-level patterns.

The study also provides important insights into the spillover effect on neighboring regions, in the aftermath of a natural disaster. While lending conditions tighten in disaster-affected states, at the aggregated state-level banks reallocate credit to neighboring states, leading to an increase in loan volume and a decrease in loan interest rates (spreads) in these regions. This suggests that financial institutions strategically shift capital away from high-risk areas toward adjacent regions, using neighboring states as financial buffers. However, as the analysis dives deeper in granularity, the credit supply effect is not fully captured. The analysis of direct versus indirect exposure reveals a distinct pattern from state-level results. In the short term, interest rates are higher for directly affected firms, while the credit supply remains inconclusive. In the long term, however, credit supply increases in these states, driven by heightened support needs and survivorship bias. Over time, interest rates decrease, with this effect being significant only for indirectly exposed firms, which are perceived as less risky. For firms in unaffected regions, both state-level and loan-level indicate a reduction in interest rates and shorter maturities. This approach helps maintain flexibility and liquidity, allowing financial institutions to support affected firms while ensuring continued lending in high-demand areas.

This study contributes to existing literature in several ways. First, my findings align with Cortés and Strahan et al. (2017), who demonstrate that credit supply increases where demand is highest, particularly in disaster-affected areas, highlighting the role of credit reallocation in disaster recovery. Javadi and Masum et al. (2021) and Correa et al. (2023) document a persistent risk premium for physical risk, but their focuses differ. Javadi and Masum (2021) examine long-term drought risk, while Correa et al. (2023) analyze the immediate effects of floods, hurricanes, and wildfires. Existing literature, such as Goss and Roberts et al. (2021), suggests that banks actively screen and prioritize high-quality firms in the post-disaster period, yet this study finds a deviation from traditional quality selection mechanisms. Rather than exclusively favoring strong firms, banks initially adjust spreads in favor of financially weaker firms, ensuring credit accessibility before reallocating resources toward more resilient firms. This study extends the literature by providing new evidence on how banks dynamically adjust pricing and non-pricing loan terms, balancing short-term risk containment with long-term credit expansion. By examining the interplay between post-disaster uncertainty, firm screening, spillover effects, and government intervention, this research offers deeper insights into how financial institutions navigate climate risk in lending decisions.

## 2. Literature Review and Hypothesis Development

### 2.1. Related Literature

Financial institutions are increasingly recognizing the risks posed by climate change to long-term economic viability and its impact on affected areas (Srobl, 2011; Vigdor, 2008). Climate risk can be categorised into three distinct classifications: firstly, physical risk, which is defined as the costs and damages caused by extreme weather events and natural disasters (Hong et al., 2019); secondly, regulatory risk, which is understood as the consequences of government policies and regulations aimed at reducing carbon emissions and combating climate change (Degryse, 2020; Fard, 2020; Chava, 2014); and thirdly, transition risk, which encompasses the potential for climate-driven innovations to disrupt established industries (Delis, 2020; Bolton, 2022). Investors are progressively incorporating environmental risks whether physical, as outlined by Pankratz et al. (2019), or transitional, as highlighted by Krueger et al. (2020) into their decision-making processes, reflecting a growing recognition of climate risk in investment decisions.

*Pricing of Climate Risk in the Financial Market*

Empirical research shows that financial markets incorporate climate risk into asset valuations, impacting equities, bonds, and real estate. Studies indicate that both transitional and physical risks influence pricing mechanisms.

In equities, climate risk carries a positive risk premium (Acharya, 2022; Hong, 2019; Bansal, 2016), though some research highlights mispricing due to climate sensitivity (Daniel, 2017; Kumar, 2019). Carbon risk is also reflected in stock returns and option markets (Ilhan, 2021; Bolton and Kacperczyk, 2021), though some evidence suggests underpricing (Garvey, 2018; In, 2019).

In bond markets, climate-related news influences yield spreads (Engle, 2020; Hyunh, 2020), with high-risk areas facing higher underwriting fees and bond yields (Painter et al., 2020). Poor environmental performance also correlates with higher spreads and lower credit ratings (Seltzer, 2021; Fard, 2020).

In real estate, findings are mixed. Sea-level rise reduces property values (Bernstein, 2019), yet some studies find no universal effect on residential prices (Murfin and Spiegel, 2020). Price adjustments depend on local climate beliefs (Baldauf, 2020). Climate risk also influences long-term discount rates (Giglio, 2018), while mortgage refinancing valuations remain unchanged despite property declines due to flooding, creating an upward bias (Gabarino, 2021).

### *Impact of Climate Risk on Firms*

Research shows that climate events significantly impact firm-level risks, financial strategies, and capital costs. While early studies focused on portfolio-level risks (Alok, 2020; Balvers, 2017), more recent research highlights firm-specific effects. Firms increase cash holdings after hurricanes as a precautionary measure (Dessaint, 2017), while drought risks raise equity costs (Huynh, 2020). Ai et al. (2023) find that climate disasters amplify both systematic and idiosyncratic risks, with industry-specific variations. Painter et al. (2020) further link these risks to investor surprises and firm performance volatility. Extreme climate conditions negatively impact corporate finances. Addoum et al. (2020) show that extreme temperatures reduce earnings, while Pankratz et al. (2019) report declines in revenue and operating income. Firms in high-risk areas adopt conservative financial strategies, such as reducing leverage (Ginglinger, 2019; Elnahas, 2018). Hsu et al. (2020) identify a pollution premium for high-emitting firms, linking environmental risk to stock returns. Investors demand higher capital costs from non-compliant firms (Chava, 2014), whereas green firms benefit from lower loan spreads when lenders are also environmentally aligned (Degryse, 2020). The relationship between climate risk, corporate finance, and credit dynamics is evident in Huynh and Nguyen et al. (2020), who show that firms exposed to physical risks face higher equity costs. Massa and Zhang (2021) find that after major disasters, firms shift from bonds to bank loans. These findings highlight how climate risk reshapes firm behavior, financing strategies, and lending patterns, with lasting implications for credit markets.

### *Climate Risk and Bank Lending*

As awareness of climate-change risks continues to grow, banks must adapt their lending practices to address these emerging challenges. Research shows that banks increasingly incorporate climate risks into their frameworks by adjusting both pricing and contractual terms. This proactive approach not only mitigates risk but also positions banks as leaders in combating climate change. For instance, studies reveal that natural disasters increase the likelihood of borrower defaults due to material losses, operational disruptions, and revenue declines. To offset these risks, banks charge higher interest rates for at-risk borrowers. Correa et al. (2023) report a significant rise in loan costs post-disaster, while Javadi and Masum et al. (2021) find higher long-term interest rates for borrowers in drought-prone areas. Similarly, Acharya et al. (2022) and Hong et al. (2019) show that banks price in physical risks such as heat stress. By leveraging pricing mechanisms to manage exposure, banks maintain profitability while accounting for climate-related risks. For example, Nguyen et al. (2022) demonstrate that mortgage interest rates increase in areas exposed to sea-level rise, reflecting a forward-looking strategy to mitigate potential property devaluation and borrower insolvency. Additionally, Baldauf et al. (2020) find that flood risk significantly affects home prices in neighborhoods where residents acknowledge climate change, underscoring the role of behavioral factors in climate risk pricing. Cogan et al. (2008), Chava et al. (2014), and Fard et al. (2020) further highlight how banks leverage loan pricing to enhance financial resilience, ensuring that climate-exposed borrowers bear higher capital costs. However, pricing mechanisms are not the sole tools banks use to mitigate risk. Credit supply adjustments also play a crucial role, though findings in academic research vary. Meisenzahl et al. (2023) show that banks reduce transaction volumes for commercial loans in high-risk areas. Conversely, Cortés and Strahan et al. (2017) find that high demand in disaster-prone regions can redirect credit away from unaffected areas toward higher-risk zones, as observed in mortgage lending. Beyond pricing, banks implement non-pricing mechanisms such as stricter loan durations, collateral requirements, and covenants for borrowers exposed to higher risks (Javadi and Masum, 2017; Dennis, 2000).

## 2.2. Hypothesis Development

This study investigates whether climate exposure, materialized through severe natural disasters, leads banks to alter lending decisions for both at-risk and non-at-risk borrowers. Extending the previous research, this study examines the impact of multiple hazard types on bank lending practices to U.S. firms. The primary focus is understanding how banks adjust loan contractual features along five key dimensions - loan size, loan spread, term-to-maturity, covenants, and collateral requirement - in response to the acute climate exposure.

As highlighted in the literature, climate risk has a significant influence on credit allocation and pricing. Research such as Meisenzahl et al. (2023) demonstrates that banks reduce transaction volumes for commercial loans in high-risk areas. In contrast, Cortés and Strahan et al. (2017) argue that increased demand in disaster-prone regions can shift credit from unaffected areas to higher-risk zones, as seen in mortgage lending. Additionally, evidence suggests that physical risks are incorporated into loan pricing through higher interest rates (Correa, 2023; Javadi and Masum, 2021), while non-pricing mechanisms, such as collateral requirements and covenants, are also employed to manage elevated physical risks (Javadi and Masum, 2017; Dennis, 2000). This leads to my first hypothesis:

**H1a.** Banks expand credit supply in regions with significant climate exposure to address high demand and support recovery efforts.

**H1b.** Banks restrict contract terms (i.e., increases pricing, shorten term-to-maturity, and includes more covenants and more collaterals) of loans to account for the risk premium associated with higher climate exposure.

Yet, high demand for credit in disaster-hit regions can lead to a redistribution of resources, which can be explained by risk mitigation concerns (Meisenzahl, 2023) and prioritizing recovery efforts during disaster events by financial institutions (Cortés, 2014; Celil, 2022, Strahan, 2017).

As observed by Cortés and Strahan et al. (2017), banks increase credit availability in disaster-hit regions, reallocating financial resources at the expense of credit contraction elsewhere. To compensate for higher exposure to riskier borrowers, banks reduce lending in unaffected regions, imposing higher spreads and shorter maturities to maintain liquidity and portfolio stability. Beyond directly affected areas, spillover regions - those bordering disaster-hit states - also experience shifts in lending behavior. Banks may either tighten contractual terms due to concerns over indirect financial instability or use these regions as financial buffers, redirecting credit away from high-risk areas. As a result, banks restrict lending terms in spillover regions while also reducing credit in unaffected states to fund disaster-hit areas, tightening lending conditions across multiple markets. This results in my second hypothesis.

**H2a.** In regions bordering disaster-hit states, banks increase credit supply but impose tighter contractual terms due to perceived spillover risk and potential indirect financial disruptions.

**H2b.** Banks reallocate credit away from unaffected regions to fund disaster-hit regions due to high demand.

Climate exposure does not affect equally; in terms of heterogeneities, borrowers with lower creditworthiness face greater challenges in adapting to climate risk. Chava et al. (2014) and Fard et al. (2020) find that these firms often experience higher costs of capital due to their environmental risk profile, exacerbating the effects on lending practices. I therefore hypothesize that

**H3.** The effects of climate exposure on lending practices are more pronounced for affected borrowers with lower creditworthiness, smaller size, and weaker profitability.

# 3. Empirical Design

## 3.1. Data

*Loan Data*

I obtained syndicated loan data from Thomson Reuters Loan Pricing Corporation, DealScan from 2000 to 2023. Following the literature I excluded financial institutions (Javadi and Masum, 2021; Flannery, 1994; Diamond, 2000). Refinitiv Loan Connector DealScan[1], formerly LPC DealScan, provides detailed information on syndicated loans, including information on lenders, borrowers, loan size, and additional deal-specific details. For each tranche, I use the all-in-spread-drawn-bps variable (the total annual spread paid over LIBOR) to measure loan interest rates. Loan amount is measured using deal values converted to U.S. dollars. Maturity is calculated as the difference between the term-to-maturity date and deal active date. Covenants are represented by a dummy variable indicating whether any financial or non-financial covenants are included, and finally, collateral is represented by a dummy indicating whether a collateral requirement is pledged in the contract. Furthermore, I collected company accounting information from Compustat, which is merged with DealScan using the link provided by Chava and Roberts et al. (2018). This integration is facilitated using the Wharton University of Pennsylvania platform, which provides the linking

[1] Loan Connector DealScan is organized into two levels: deals and tranches. A 'deal' corresponds to a 'package' in the legacy DealScan. Similarly, a 'tranche' corresponds to a 'facility' in legacy DealScan, identifying individual components within a loan deal (or package). In Loan Connector DealScan, the 'deal' identifier tracks a loan agreement and assigns the same Deal ID to subsequent amendments, allowing for the tracking of historical changes to the loan agreement over time. Merging the Legacy DealScan and Loan Connector DealScan datasets was a detailed process. It needed careful data cleaning and the use of WDRS linking tables to help with the integration. I first reconciled differences in variable formats, made sure identifiers were consistent across both datasets, and fixed any missing or duplicate entries. The WDRS linking tables helped on accurately matching records from both datasets. This process highlighted the complexity and attention to detail required for a successful merge.

tables between Legacy DealScan and Loan Connector DealScan. The average loan tranche has a size of about USD 494 million and matures in about 11 months. The average spread is about 223 bp (LIBOR). About 52% of the loans in the sample include covenants.

*Climate Data*

The climate risk database was retrieved from Spatial Hazard Events and Losses Database for the United States (SHELDUS)[2], which provides a county-level hazard database, including different natural hazard types such as blizzards, floods, wildfires and hurricanes. Following the methodology outlined by Javadi and Masum et al. (2021), the data was aggregated at the state level. For each event, the database includes the start date, location (state), property losses, crop losses, injuries and fatalities that affected each state. The sample includes reports on "Named Events" in SHELDUS that occurred in the United States between 2000 and 2023. SHELDUS does not include all hazards but only the most relevant events reported in that category. Table 1 reports the summary statistics on the number of records, total damage (property plus crop damage), and the distribution of damage across the database by hazard type. To simplify the analysis, I grouped the hazards into seven categories, following Cortés and Strahan et al. (2017): Coastal (including "Coastal" and "Tsunami/Seiche" due to only having 1 record), Flooding (including "Flooding" and "Landslide"), Hurricane (including "Hurricane" and "Wind"), Tornado, Heat (including "Heat", "Wildfire" and "Drought"), Blizzard (including "Blizzard", "Winter Weather", "Avalanche" and "Fog") and Severe Storm (including "Severe Storm", "Hail" and "Lightning"). There are 15955 records across all hazards. Flooding is the most devastating, causing USD 385.98 billion in damage across all states despite fewer records (2029), indicating that this type of hazard is heavily damaging. This is followed by hurricanes, with USD 347.56 billion in damage across 3539 records. Heat events come next, with USD 288.80 billion in damage reported across 3056 records, followed by Severe Storms, with USD 80.51 billion in damage across 5255 records. Finally, Blizzard and Costal events have incurred in a combined USD 4.82 billion in damage over 539 records.

[2] See https://cemhs.asu.edu/sheldus

***Table 1 Damage across natural hazards***

This table reports data on damage losses (including monetary losses to property and crops) resulting from natural disasters taken from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). This sample reports all the available "named events" of natural hazards reported in SHELDUS that occurred in the U.S. states between 2000 and 2023 on state-level monthly aggregation.

| | | | *Damage (in millions)* | | | | |
|---|---|---|---|---|---|---|---|
| *Hazard Type* | *Number of records* | *Damage across all states (billions)* | *p25* | *median* | *p75* | *p95* | *p90* |
| Blizzard | 404 | 4.59 | 0.01 | 0,08 | 1.11 | 28.73 | 509.38 |
| Coastal | 135 | 0.23 | 0.00 | 0,00 | 0.00 | 0.31 | 42.80 |
| Flooding | 2029 | 385.98 | 0.02 | 0.32 | 4.72 | 209.42 | 1272.49 |
| Heat | 3056 | 288.80 | 0.01 | 0.54 | 28.60 | 350.94 | 1493.35 |
| Hurricane | 3539 | 347.56 | 0.02 | 0.13 | 0.70 | 64.39 | 2073.49 |
| Severe Storm | 5255 | 80.51 | 0.02 | 0.09 | 0.51 | 11.99 | 534.06 |
| Tornado | 1537 | 56.82 | 0.10 | 0.57 | 3.60 | 92.02 | 942.86 |
| *All Hazards* | *15955* | *1164.49* | | | | | |

To measure climate loss exposure, I constructed a monthly climate exposure index for each state over time in the following steps.

For each state, month, and year, all recorded hazards were aggregated. The magnitude of shocks was captured by using cumulative total damage calculated over the m (m = 0, 1, 3, 6, 9, 12, 18 and 24) months following the disaster.

$$Climate\ Exposure_m = \left(\frac{Damage\ Cum_m}{GDP_m}\right) \tag{1}$$

Next, I extracted the annual GDP by state from the U.S Bureau of Labor Statistics[3] and estimated monthly GDP values by assuming an equal distribution over the studied rolling window. Lastly, I scaled the cumulative total damage by the corresponding monthly cumulative GDP. This approach ensures that the climate variable proxy reflects the relative risk rather than isolated events, enhancing comparability across states with varying economic sizes and levels of development. It provides a robust foundation for investigating how banks adjust lending decisions.

*Macroeconomic Data*

For this study, I collected the annual state-level GDP from 2000 to 2023 and subsequently converted it into monthly GDP estimates by state to improve temporal granularity. Additionally, I collected the percentage growth for state GDP, state employment, state personal income and state personal consumption expenditure in the United States. Incorporating variables significantly

[3] See https://www.bls.gov/

enhances the rigor of the analysis by accounting for macroeconomic variations and economic cycles that impact lending practices, such as economic activity, labor market conditions, income levels, and consumer spending patterns across states, thereby mitigating confounding effects.

*Firm Financial Statements Data*

In this research, I collected firm financial statement data from Compustat to control for borrower-specific characteristics that may impact banks' lending decisions. Following Javadi and Masum et al. (2017), I retrieved the annual financial fundamentals of listed companies that include the variables asset size, profitability (ROA), book-to-market and leverage and subsequently, merged Compustat with DealScan using a one-year lag in the Compustat database. This approach ensures that the financial measures used in the analysis reflect the information available to lenders at the time of the loan decision, as banks typically base their lending decisions on the borrower's financial performance in the previous year. This lagged integration allows for more accurate assessment of the relationship between borrower characteristics and loan terms. To enhance the robustness of the analysis and mitigate the influence of extreme values, I winsorize all variables at 1 and 99 percentiles. This method preserves the overall distribution while reducing the impact of outliers on the results.

*Government disaster-loans data*

This study gathers data on government disaster loans data from the Federal Emergency Management Agency (FEMA)[4] platform to account for potential noise in the mechanism through which banks channel credit incentives from governmental regulations. Since this information is highly restricted, this study uses FEMA loans as a proxy. More specifically, I aggregate disaster loans at the state-month level and match them with the DealScan database. FEMA and SBA loans are distinguished by their provision of low-interest disaster loans.

[4] See https://www.fema.gov/

*Table 2 Summary Statistics*

This table reports summary statistics for key variables in the sample, combining data from the Climate Database, DealScan and Compustat on state-level monthly aggregation. Detailed descriptions of the variables can be found in Table 6 of the Appendix.

| | Mean | SD | Min | Max | P(25) | P(75) |
|---|---|---|---|---|---|---|
| *Physical Risk Data* | | | | | | |
| Direct Exposure | 0.100 | 3.700 | 0.000 | 448.100 | 0.000 | 0.000 |
| Indirect Exposure | 1.300 | 23.700 | 0.000 | 1033.400 | 0.000 | 0.000 |
| *Loan Data* | | | | | | |
| Deal_amount | 5.161 | 1.615 | 0.215 | 13.218 | 4.111 | 6.217 |
| Spread (in pp.) | 2.234 | 1.767 | 0.018 | 17.500 | 1.100 | 2.870 |
| Maturity | 3.689 | 0.763 | 0.065 | 5.904 | 3.233 | 4.126 |
| Covenants | 0.516 | 0.500 | 0.000 | 1.000 | 0.000 | 1.000 |
| Collaterals | 0.464 | 0.499 | 0.000 | 1.000 | 0.000 | 1.000 |
| *Macroeconomic Data* | | | | | | |
| State GDP (monthy) | 62255.140 | 51443.168 | 1622.258 | 322531.575 | 24573.033 | 89355.983 |
| %g state employment | 1.129 | 1.783 | -6.900 | 8.000 | 0.100 | 2.300 |
| %g state personal c. expenditure | 4.706 | 2.452 | -4.900 | 16.000 | 3.600 | 5.900 |
| %g state personal income | 4.505 | 2.796 | -7.700 | 12.700 | 2.900 | 6.300 |
| %g state GDP | 4.569 | 3.119 | -15.000 | 16.700 | 3.000 | 6.100 |
| *Firm Data* | | | | | | |
| ROA | 0.002 | 0.193 | -1.134 | 0.300 | -0.008 | 0.076 |
| Log(total_assets) | 7.130 | 2.097 | 2.045 | 11.732 | 5.751 | 8.527 |
| Log(lev) | -1.358 | 1.349 | -7.033 | 0.225 | -1.761 | -0.583 |
| B/M | 2.585 | 2.359 | 0.586 | 8.248 | 1.170 | 2.608 |
| Z_Score | 5.515 | 6.870 | -5.243 | 27.667 | 1.779 | 5.385 |
| *Disaster Loans Data* | | | | | | |
| Disaster-loans (in millions) | 7.620 | 143.192 | 0.000 | 13630.462 | 0.000 | 0.000 |
| Observations | 15435 | | | | | |

Figure 2 in the Appendix illustrates the relationship between disaster-related damage and FEMA disaster loans from 2000 to 2023. Monetary losses, including property and crop damage, reflect the financial impact of natural hazards, while disaster loans represent federal relief. The most severe spikes occurred in 2005 and 2017, aligning with major disasters, highlighting the link between large-scale events and government aid. In 2005, multiple hurricanes devastated the Gulf Coast. In 2012, Superstorm Sandy impacted New Jersey and New York, alongside a severe drought affecting over half the country. The 2017-2018 period saw catastrophic flooding, hurricanes, and wildfires causing widespread destruction.

Figure 3 in the Appendix visualizes natural hazard exposure and its impact on credit supply across the U.S. The first map captures exposure using a cumulative 12-month rolling window, while the second depicts percentage changes in deal amounts. The selected years (2006, 2013, and 2018) correspond to heightened climate exposure. Generally, states with greater climate exposure experience a decline in credit supply, though exceptions exist. Despite severe exposure, Louisiana (2005-2006) and Texas (2017-2018) saw a credit supply increase, suggesting financial institutions meet rising credit demand post-disaster. As shown in Figure 4, FEMA loan allocations - USD 14.31 billion for Louisiana (2005) and USD 2.92 billion for Texas (2017) - align with periods of stable credit supply despite significant hazard exposure. This suggests federal aid helps sustain post-disaster credit availability.

## 3.2. Methodology

This study investigates the impact of climate exposure on lending dynamics at both state and loan levels, employing a fixed effects regression framework to capture for unobserved heterogeneities. By incorporating both state-level and loan-level analysis, this study provides insights into the complementary dimensions on lending behavior, including credit supply adjustments, risk-pricing mechanisms, and other non-pricing mechanisms in response to climate shocks. It employs state-level aggregated damage as a proxy for climate exposure to assess whether banks systematically adjust lending to firms headquartered in disaster-prone areas.

At state-level, the regression analysis examines aggregated lending patterns by computing the total number of loans issued within each state, the total loans amounts, the average interest rates (spreads) across all loans, and the average values of covenants and collateral requirements. In this specification, $Y_{s,t}$ denotes the lending conditions of loans issued in state s, in time t by bank b. To account for potential macroeconomic variations, the specification includes state-level economic controls, ensuring fluctuations in economic activity do not drive observed lending behavior. Additionally, bank fixed effects are incorporated to control unobserved heterogeneity across financial institutions, ensuring that differences in risk appetite, capital structures, and operational strategies do not bias the results. By aggregating lending data at the state-level, this approach captures extensive margin effects, reflecting how banks collectively adjust credit availability in response to climate exposure. This enables the identification of systemic shifts in credit allocations and risk pricing across regions over time.

$$Y_{s,t} = \alpha + \beta\ Climate\ Exposure_{s,t} + \gamma\ Macroeconomic\ Controls\ _{t-1} + BankFE_b + \varepsilon_{s,t} \tag{2}$$

The loan-level analysis provides a more granular perspective by focusing on how banks modify individual loan contracts in response to climate risks. This dimension primarily captures the intensive margin, assessing changes in loan size, spreads, maturity, covenants, and collaterals requirements. Unlike the state-level analysis, which captures broader lending adjustments, specifically credit supply availability, the loan-level approach highlights how financial institutions adjust specific contractual terms for borrowers facing climate-related risks. By examining firm-specific lending conditions, this analysis helps uncover how banks navigate climate exposure at the contract level, complementing the broader trends observed at the state-level. The baseline specification used in this study is as follows:

$$\begin{aligned} Y_{i,b,j,s,t} = {} & \alpha + \beta\ Climate\ Exposure_{s,t} + \gamma\ Macroeconomic\ Controls\ _{t-1} + \delta\ Firm\ Controls_{j,t-1} + FirmFE_j \\ & + Loan\ Purpose_i + Loan\ Type_i + BankFE_b + \varepsilon_{i,\mathrm{b,j},s,t} \end{aligned} \tag{3}$$

In this specification, $Y_{i,b,j,s,t}$ denotes the deal amount, spreads, maturity, covenants and collaterals of loan i, issued in state s, in time t, to firm j by bank b. My parameter of interest is β, measures the effect of physical risk exposure (i.e. cumulative property damage scaled by the corresponding monthly cumulative GDP) on lending decisions to firms in the United States.

Following previous literature (Javadi and Masum, 2021; Chava, 2014) this regression includes a wide range of control variables that may influence loan contractual features.

The first set of these variables controls macroeconomic characteristics (γ) and includes the percentage growth of GDP and total employment to capture within-year variations related to the economic cycle and labor market conditions. Additionally, the percentage growth of personal income and personal consumption expenditures is included to control for inflationary pressures affecting purchasing power and credit demand. During periods of low GDP or low employment growth, banks adopt more cautious lending practices by reducing loan amounts due to higher uncertainty of borrowers' repayment capacity and less demand, as firms face fewer investment opportunities in a slower economy. Interest rates (spread) increase due to heightened credit risk and intensified competition among borrowers for limited credit. Loan maturities are shorten, while covenants and collateral requirements tighten to limit exposure and enhance borrower monitoring. In contrast, during periods of high GDP or employment growth, banks increase loan amounts, lower spreads due to reduced risk perception and competition, extend maturities to support long-term investments, and loosen covenants and collateral requirements as borrower confidence improves. When personal income and consumption growth slows down, inflationary pressures may decline, leading to lower interest rates and making borrowing more affordable, despite tighter lending conditions. Conversely, when personal income and consumption growth accelerate, inflationary pressures may rise, potentially leading to higher interest rates as central banks tighten monetary policy to control inflation.

The second set controls borrower-specific characteristics from the previous year that impact lending decisions, including firm size (log total assets), profitability (ROA), book-to-market, and leverage. As Javadi and Masum et al. (2021) highlighted, larger firms face fewer financing constraints and information asymmetry, making them more likely to obtain larger deal amounts and lower spreads. Firms with high leverage are associated with greater default risk and are likely to face higher spreads and stricter covenants. Profitability is also critical, as more profitable firms are less likely to default. Similarly, firms with higher book-to-market ratios tend to have stronger valuations and greater growth potential (Hovakiaman, 2006), improving their chances of securing larger loans on better terms.

Lastly, firm[5], bank[6], loan type[7], loan purpose[8] fixed effects capture time-invariant characteristics of borrowers, lenders, and loan structures. Bank fixed effects account for risk appetite, credit policies, and operational practices (Javadi and Masum, 2021; Gropp, 2019; Krosner, 2001; Goss and Roberts, 2011). Loan type and purpose fixed effects control for variations in contractual

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[5] Firm FE controls for time invariant firm characteristics, ensuring results are not biased by unobserved heterogeneity in borrower. Identifies within-firm variation.

[6] . Bank FE restrict identification to within-bank variation.

[7] Loan Purpose: (=1, if the purpose is to spend in acquisitions, buyout, merger, spinoff, takeover; =2, if the purpose is to spend in general purpose; =3, if the purpose is to spend in financial purposes; and =4, if the purpose is to spend in others). Eliminates variation coming from different loan structures.

[8] Loan Type: (=1, if type of borrowing is a term loan; =2, if type of borrowing if a line loan; =2, if type of borrowing is a letter-of-credit; =2, if the type of borrowing is a 364-day facility). Eliminates variation coming from different loan purposes.

features, particularly pricing and structure. To account for this variation, I include deal purpose and loan type, following Ivashina et al. (2019). Finally, firm fixed effects capture borrower-specific characteristics.

*Credit Reallocation and Spillover Effects*

To test whether banks reallocate credit across regions in response to climate shocks, I extended the baseline model for both state and loan levels by incorporating an indirect climate exposure measure, which captures spillover effects from neighboring states:

$$\begin{cases} Y_{i,s,t} = \alpha + \beta\ Climate\ Exposure_{s,t} + \theta\ Indirect\ Climate\ Exposure_{s,t} + \gamma\ X_{i,s,t-1} + \lambda + \varepsilon_{i,s,t} \\ IndirectClimate\ Exposure_{s,t,n} = \sum Cimate\ Exposure_{1}^{n,t} \end{cases} \tag{4}$$

Where $Indirect\ Climate\ Exposure_{n,s,t}$ aggregates climate damage from bordering states, n at time t. The variable $X_{i,s,t-1}$ denotes for the controls and $\lambda$ represents the fixed effects. This model is estimated at both the state and loan levels, allowing to test whether banks (1) increase or decrease lending (2) loosen or tighten lending conditions in neighboring states that share borders with regions affected by climate events. A significant θ would indicate that borrowers in bordering states, though not directly impacted by a natural disaster, experience changes in lending conditions. Finally, to investigate whether banks adjust lending decisions in regions unaffected by climate disaster, either directly or indirectly, I introduce an alternative specification:

$$Y_{i,s,t} = \alpha + \beta\ Climate\ Exposure_{s,t} + \theta\ Unaffedted_{s,t} + \gamma X_{i,s,t-1} + \lambda + \varepsilon_{i,s,t} \tag{5}$$

Where $Unaffedted_{s,t}$ is a dummy variable that is equal to 1 if a state neither experiences a natural disaster in time t, nor shares borders with affected states, s. The model is estimated at both state and loan levels, following the same approach as previous specifications.

*The Role of Government Support*

Lastly, I assess whether the presence of disaster relief loans moderates the effect of climate exposure on loan size and interest rates (spread). This is tested by introducing a dummy variable that equals 1 if disaster loan programs were issued in state s at time t.

$$Y_{i,s,t} = \alpha + \beta\, Climate\ Exposure_{s,t} + \theta\, DisasterLoans_{s,t} + \mu\, DisasterLoans_{s,t}\ x\ Climate\ Exposure_{s,t} + \gamma X_{i,s,t-1} + \lambda + \varepsilon_{i,s,t} \tag{6}$$

Where the interaction term $DisasterLoans_{s,t}\ x\ Climate\ Exposure_{s,t}$ tests whether disaster relief mitigates the effects of climate exposure on lending. A significant positive coefficient on μ would indicate that disaster relief offsets these tightening effects.

# 4. Results

## 4.1. Main Results

I begin by examining how climate exposure influences lending dynamics by analyzing changes in lending standards over time. The regressions framework used to explore these relationships is specified in Equations 2 and 3, with the results provided in Table 3. This table tracks the evolution of key lending parameters, capturing shifts in credit conditions from the immediate post-disaster period to a cumulative 24-month rolling window following a natural hazard.

Panel A of Table 3 reports the results aggregated at the state level, incorporating macroeconomic controls and bank fixed effects. The findings indicate that financial institutions limit credit conditions in states highly exposed to natural hazards, both in the short and long run. The number of loans declines significantly at t0, t1, t3, t6, t12, and t24, indicating that as disasters unfold, their cumulative impact further restricts lending. Similarly, credit supply contracts significantly from t0 to t9 and t24, as banks reduce loan sizes in affected states. This suggests that financial institutions reduce both the number and volume of loans to borrowers headquartered in affected states due to heightened credit risk and uncertainty. To compensate for this risk, banks increase loan pricing (spreads) sharply at t0 (0.894**), with the effect becoming more pronounced over time (t24 =

3.832***), indicating that lenders impose higher risk premiums on disaster-exposed regions, making borrowing more expensive. This aligns with prior research on post-disaster credit risk (Javadi and Masum, 2021; Correa, 2023). Secondary lending terms also adjust in response to rising exposure. Collateral requirements and maturity increase, while covenants decline post-disaster, particularly beyond t9, potentially reflecting a shift in banks' risk-mitigation approach toward asset-backed security rather than contractual restrictions.

Panel B extends the analysis to the loan-level. This specification incorporates additional firm-specific characteristics, including size (log assets), leverage, book-to-market ratio, and return on assets, along with firm, loan type, and loan purpose fixed effects. By examining the same firms exposed to varying levels of natural hazard exposure, this approach mitigates biases arising from unwanted variation. Columns (1), (3), (5), (7), and (9) report values without firm fixed effects, allowing for a comparison across firms. The results indicate that banks do not immediately adjust contract amount, maturity and covenants following a disaster. Instead, their initial response is to increase interest rates (spreads), as is shown in the significantly positive coefficient at t0 (0.799***) and t1 (1.600***), highlighting significant post-disaster volatility and uncertainty regarding economic recovery. The results remain consistent after incorporating firm fixed effects. To manage climate exposure, banks impose higher interest rates on at-risk borrowers while maintaining post-disaster credit supply. This suggests that financial institutions capitalize on the post-shock period by charging higher premiums on loans to high-exposed borrowers. However, over time, the relationship between loan size and climate exposure declines, reflecting stabilization in volatility, economic recovery efforts and potential government and insurance interventions. In the long run, more particularly on t12 (1.711**) and t18 (2.299**), lending patterns shift, with evidence of an increase in credit supply at lower interest rates (spreads) - turning negative at t24 (-3.856**). Moreover, this effect is only significant when firm fixed effects are included, suggesting that banks may be offering more favorable terms to the same firms over time. This could be attributed to banks identifying resilient borrowers who successfully navigated the post-disaster period or those with strong government or insurance backing, making them lower-risk and more attractive borrowers in the long run. Additionally, the decline in volatility over time, along with fading post-disaster momentum, contributes to the normalization of lending standards. This transition highlights two key mechanisms: 1) the diffusions of the post-disaster shock and 2) the screening of firms that successfully “survived” the post-disaster shock period. Indeed, over time banks are able to identify borrowers who have demonstrated resilience, now perceived as lower-risk and more attractive to lenders, which makes financial institutions more willing to extend credit. The mechanism illustrates how banks adjust their strategies in response to evolving risk and recovery dynamics, balancing short-term risk pricing with longer-term lending opportunities. Maturity, covenants and collateral requirements follow the state-level results, as collaterals and maturity remain positive, while covenants remain negative in the long-run.

These findings suggest that, at the aggregate level, financial institutions reduce both the number and volume of loans. However, this effect is not fully captured at the loan-level. While the aggregate analysis captures a decline in credit supply (extensive margin) to directly affected regions, the loan-level analysis provides insight into how loan terms adjust (intensive margin). This dual approach offers complementary perspective, enhancing the understanding of lending behavior in response to external shocks.

This study contributes to existing literature in several ways. First, my results align with Cortés and Strahan et al. (2017), who show that credit supply increases where demand is highest, particularly in disaster-affected areas and highlight the role of credit reallocation in disaster recovery. Javadi and Masum (2021) and Correa et al. (2023) document a persistent risk premium for physical risk, but their focus differs. Javadi and Masum (2021) examines long-term drought risk, while Correa et al. (2023) analyzes the immediate effects of floods, hurricanes, and wildfires. Existing literature, such as Goss and Roberts et al. (2021), also suggests that banks actively screen and prioritize high-quality firms in the post-disaster period, yet this study finds a deviation from traditional quality selection mechanisms. Rather than exclusively favoring strong firms, banks initially adjust spreads in favor of financially weaker firms, ensuring credit accessibility before reallocating resources toward stronger firms. This study extends the literature by providing new evidence on how banks dynamically adjust pricing and non-pricing loan terms over time, balancing risk containment in the short term with credit expansion in the long term. By identifying the interplay between post-disaster uncertainty, firm screening, spillover effects, and government intervention, this research offers deeper insights into how financial institutions navigate climate risk in lending decisions.

***Table 3 Lending Standards and Climate Exposure: A Temporal Perspective***

This table presents the contractual terms: number of loans, size, spread, maturity, covenants and collateral requirements as a function of the temporal perspective from the disaster-hit moment until the accumulated previous 24 months on total loss scaled by state GDP. Panel A reports the results on state-level and Panel B on loan-level. All columns in Panel A include macroeconomic controls and incorporate Bank FE. All columns in Panel B include macroeconomic and firm-specific controls and incorporate Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01

Panel A

| | Lending Dynamics: Direct Climate Exposure | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Disaster Window | Number of Loans | Size | Spreads | Maturity | Covenants | Collaterals |
| t0 | -3.225*** | -0.987*** | 0.894*** | 0.230** | -0.144** | 0.118* |
| | (1.160) | (0.303) | (0.237) | (0.105) | (0.068) | (0.069) |
| t1 | -4.972** | -1.389** | 1.809*** | 0.376* | -0.324** | 0.191 |
| | (2.185) | (0.571) | (0.447) | (0.197) | (0.128) | (0.129) |
| t3 | -4.275* | -1.316** | 1.384*** | 0.315 | -0.046 | 0.278** |
| | (2.237) | (0.585) | (0.528) | (0.202) | (0.131) | (0.132) |
| t6 | -6.872* | -2.009** | 2.687*** | 0.579* | -0.190 | 0.431* |
| | (3.794) | (0.991) | (0.887) | (0.343) | (0.223) | (0.224) |
| t9 | -7.305 | -2.351* | 3.045*** | 0.845** | -0.338 | 0.460 |
| | (4.732) | (1.236) | (1.067) | (0.428) | (0.278) | (0.280) |
| t12 | -7.274* | -1.336 | 1.330 | 0.719* | -0.411* | 0.745*** |
| | (4.102) | (1.072) | (0.873) | (0.371) | (0.241) | (0.242) |
| t18 | -8.795 | -1.895 | 3.080*** | 1.094** | -0.336 | 1.310*** |
| | (5.395) | (1.410) | (1.140) | (0.488) | (0.317) | (0.319) |
| t24 | -11.059* | -3.079** | 3.832*** | 1.055** | -0.979*** | 1.253*** |
| | (5.862) | (1.532) | (1.226) | (0.530) | (0.344) | (0.346) |
| BankFE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 12759 | 12759 | 12675 | 12445 | 12759 | 12759 |
| $R^2$ | 0.183 | 0.169 | 0.187 | 0.197 | 0.122 | 0.120 |

| Panel B | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lending Dynamics: Direct Climate Exposure | | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Disaster Event | Size | | Spreads | | Maturity | | Covenants | | Collaterals | |
| | No FE | FE | No FE | FE | No FE | FE | No FE | FE | No FE | FE |
| t0 | 0.012 | 0.110 | 0.645** | 0.799*** | 0.155 | 0.172 | -0.153 | -0.101 | 0.089 | 0.045 |
| | (0.216) | (0.184) | (0.281) | (0.251) | (0.148) | (0.157) | (0.095) | (0.096) | (0.093) | (0.082) |
| t1 | 0.155 | 0.312 | 1.185** | 1.600*** | 0.271 | 0.339 | -0.352** | -0.213 | 0.153 | 0.053 |
| | (0.402) | (0.351) | (0.525) | (0.483) | (0.275) | (0.301) | (0.177) | (0.184) | (0.172) | (0.156) |
| t3 | 0.525 | 0.257 | 0.653 | 0.325 | 0.262 | 0.312 | -0.167 | -0.145 | 0.193 | 0.196 |
| | (0.414) | (0.354) | (0.620) | (0.560) | (0.283) | (0.303) | (0.183) | (0.185) | (0.178) | (0.157) |
| t6 | 0.738 | 0.481 | 1.514 | 0.713 | 0.536 | 0.575 | -0.390 | -0.252 | 0.270 | 0.264 |
| | (0.702) | (0.604) | (1.043) | (0.954) | (0.480) | (0.518) | (0.310) | (0.316) | (0.301) | (0.269) |
| t9 | 1.026 | 1.115 | 1.575 | -0.425 | 0.780 | 0.810 | -0.529 | -0.401 | 0.200 | 0.153 |
| | (0.873) | (0.755) | (1.252) | (1.160) | (0.597) | (0.648) | (0.386) | (0.396) | (0.375) | (0.336) |
| t12 | 1.869** | 1.711** | -0.327 | -1.695 | 0.966* | 1.189* | -0.528 | -0.732* | 0.470 | 0.496 |
| | (0.746) | (0.743) | (1.027) | (1.096) | (0.510) | (0.637) | (0.329) | (0.389) | (0.320) | (0.331) |
| t18 | 2.327** | 2.299** | 0.758 | -1.280 | 1.264* | 1.547* | -0.637 | -0.573 | 0.820* | 1.158*** |
| | (0.983) | (0.982) | (1.344) | (1.447) | (0.673) | (0.842) | (0.434) | (0.515) | (0.422) | (0.438) |
| t24 | 2.991*** | 1.525 | 0.562 | -3.856** | 1.666** | 1.363 | -1.102** | -1.070* | 0.691 | 0.973* |
| | (1.074) | (1.124) | (1.445) | (1.631) | (0.734) | (0.964) | (0.474) | (0.589) | (0.461) | (0.500) |
| BankFE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Obs. | 14695 | 12729 | 12682 | 10802 | 14053 | 12092 | 14696 | 12730 | 14696 | 12730 |
| $R^2$ | 0.633 | 0.837 | 0.473 | 0.760 | 0.253 | 0.523 | 0.274 | 0.573 | 0.311 | 0.688 |

## 4.2. Credit Flows and Reallocation

Table 4 presents the regression results for indirect climate exposure, outlined in Equation 4, investigating how lending conditions adjust in states bordering disaster-affected regions. The analysis examines its impact on state-level credit dynamics (Panel A) and loan-level lending conditions (Panel B).

Panel A reports the regression results at the state-level. The findings reveal a notable decomposition effect in lending terms, particularly in the number of loans, size, and spread. While direct exposure leads to a decline in these variables, the indirect exposure variable often shows an increase, suggesting that banks offset reductions in lending to disaster-affected states by reallocating credit to their neighboring states. This pattern highlights a spillover effect on credit markets, where banks shift capital away from high-risk areas toward adjacent regions. This decomposition effect is particularly evident in the number of loans, where the direct exposure regression shows a significant decline, from t0 (-4.565***) to t24 (-53.732***). Conversely, under indirect exposure, the number of loans increases, from t0 (0.948***) to t24 (38.744***).

A similar pattern is observed in loan size, where the direct exposure coefficients indicate contraction, while indirect exposure coefficient suggest an increase, mitigating the impact on overall credit availability. Additionally, the statistically significant and magnitude of the coefficients are, on average, stronger for indirect exposure, indicating that banks actively reallocate credit flow to neighboring states. This suggests that financial institutions not only respond to risk by reducing credit in directly affected areas but also strategically compensate for this reduction in border-sharing regions, likely to sustain overall lending volumes and mitigate economic disruptions in these regions. If banks reduce lending in high-exposed states, they are expected to compensate by increasing lending elsewhere, both to rebalance their portfolios and to support indirectly affected economies.

This is also reflected in interest rates (spreads), where indirect exposure leads to lower interest rates, suggesting that loans to neighboring states benefit from improved financing conditions as their risk profiles adjust locally. Furthermore, maturity and collaterals requirements remain positive under both direct and indirect exposure, indicating that banks continue to impose stricter collaterals constraints to mitigate risk. However, in contrast to direct exposure (Table 3), covenants tend to strengthen under indirect exposure, suggesting that banks closely monitor neighboring borrowers, ensuring financial risk remains manageable despite increased and favorable lending activity.

Panel B presents the regression results for indirect climate exposure at the loan-level. After introducing firm-level controls and fixed effects, the coefficient for indirect exposure on loan size is insignificant, suggesting that firm-specific factors absorb the spillover effect. This implies that banks do not only reallocate credit geographically but also adjust lending based on firms' risk profiles and financial stability. While spreads remain significantly affected, their magnitude declines compared to state-level results. Banks impose higher interest rates in directly exposed states immediately after a disaster (e.g., t0 = 0.756*), while spreads are lower under indirect exposure. Over time, the divergence between direct and indirect exposure becomes particularly notable at t12 and t24. For directly exposed regions, spreads remain significantly positive, whereas for indirectly exposed regions, spreads decline and eventually turn negative. This suggests that banks initially charge higher interest rates to directly affected states due to immediate disaster-related risks but gradually reassess risk and lower spreads for indirectly affected regions as time progresses. This finding implies that banks apply differentiated risk pricing, incorporating firm-specific financial stability into lending decisions. This aligns with the results presented in Table 3, which highlight a short-term pricing mechanism followed by long-term credit extensions at lower costs to surviving or government-backed firms.

Maturity and collateral requirements continue to rise, though to a lesser extent than at the state-level, indicating that loan purpose, loan type, and firm characteristics moderate these effects. Meanwhile, covenants remain unchanged, reinforcing that banks maintain safeguards without uniformly tightening contract terms across all lending agreements. The spillover effect from bordering states is evident at both state and loan levels, but firm and loan characteristics absorb some of the risk, leading to a less pronounced credit reallocation effect due to climate exposure. While banks reduce lending in directly exposed states, they selectively expand credit in neighboring states, often at better pricing conditions. Once again, the results provide a complementary analysis at both levels of aggregation. While the loan-level analysis does not fully capture these effects, the state-level aggregation highlights the extensive margin effects, offering a broader macro perspective on lending patterns. This reveals a reduction in total amounts and volumes of loans in directly affected regions, with credit being redirected to neighboring areas where demand is high, but borrowers are not directly affected.

***Table 4 Spillover Effects of Indirect Climate Exposure: A Temporal Perspective on Border-Sharing***

This table presents the contractual terms: number of loans, size, spread, maturity, covenants and collateral requirements as a function of the temporal perspective from the indirect climate exposure from disasters in neighboring states. Panel A reports the results on state-level and Panel B on loan-level. All columns in Panel A include macroeconomic controls and incorporate Bank FE. All columns in Panel B include macroeconomic and firm-specific controls and incorporate Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01.

Panel A

| | Lending Dynamics: Indirect Climate Exposure | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (8) | (9) |
| Disaster Event | Number of Loans | | Size | | Spreads | | Maturity | | Covenants | | Collaterals | |
| | Direct | Indirect | Direct | Indirect | Direct | Indirect | Direct | Indirect | Direct | Indirect | Direct | Indirect |
| t0 | -4.565*** | 0.948*** | -1.273*** | 0.214*** | 0.954*** | -0.043 | 0.175* | 0.041** | -0.164** | 0.015 | 0.111 | -0.001 |
| | (1.215) | (0.204) | (0.307) | (0.052) | (0.240) | (0.040) | (0.105) | (0.018) | (0.069) | (0.012) | (0.069) | (0.012) |
| t1 | -6.188*** | 0.704** | -1.779*** | 0.274*** | 1.916*** | -0.101* | 0.292 | 0.065*** | -0.343*** | 0.024 | 0.177 | -0.003 |
| | (2.261) | (0.280) | (0.571) | (0.071) | (0.447) | (0.055) | (0.195) | (0.024) | (0.128) | (0.016) | (0.129) | (0.016) |
| t3 | -8.814*** | 4.044*** | -2.025*** | 0.622*** | 1.495*** | -0.109 | 0.172 | 0.119*** | -0.111 | 0.074*** | 0.240* | 0.028 |
| | (2.336) | (0.452) | (0.591) | (0.114) | (0.532) | (0.089) | (0.202) | (0.039) | (0.132) | (0.026) | (0.134) | (0.026) |
| t6 | -16.397*** | 8.271*** | -3.459*** | 1.254*** | 2.891*** | -0.218* | 0.444 | 0.094* | -0.273 | 0.109*** | 0.330 | 0.073** |
| | (3.921) | (0.618) | (0.994) | (0.157) | (0.889) | (0.122) | (0.341) | (0.054) | (0.223) | (0.035) | (0.225) | (0.035) |
| t9 | -19.490*** | 10.706*** | -4.188*** | 1.654*** | 3.122*** | -0.145 | 0.808* | 0.021 | -0.444 | 0.125*** | 0.265 | 0.148*** |
| | (4.884) | (0.771) | (1.239) | (0.196) | (1.069) | (0.153) | (0.425) | (0.067) | (0.278) | (0.044) | (0.280) | (0.044) |
| t12 | -28.616*** | 17.539*** | -4.297*** | 2.690*** | 1.316 | -0.092 | 0.674* | 0.014 | -0.635*** | 0.148*** | 0.438* | 0.231*** |
| | (4.180) | (0.865) | (1.066) | (0.221) | (0.870) | (0.173) | (0.367) | (0.076) | (0.240) | (0.050) | (0.242) | (0.050) |
| t18 | -39.866*** | 26.320*** | -5.850*** | 3.705*** | 3.038*** | -0.011 | 1.027** | 0.028 | -0.704** | 0.253*** | 0.781** | 0.419*** |
| | (5.446) | (1.054) | (1.397) | (0.270) | (1.134) | (0.212) | (0.482) | (0.093) | (0.314) | (0.061) | (0.317) | (0.061) |
| t24 | -53.732*** | 38.744*** | -8.556*** | 5.278*** | 3.884*** | -0.170 | 0.868* | 0.177* | -1.340*** | 0.289*** | 0.606* | 0.551*** |
| | (5.839) | (1.170) | (1.517) | (0.304) | (1.225) | (0.239) | (0.525) | (0.105) | (0.343) | (0.069) | (0.345) | (0.069) |
| BankFE | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Obs. | 14153 | | 14153 | | 13803 | | 14056 | | 14153 | | 14153 | |
| $R^2$ | 0.255 | | 0.201 | | 0.206 | | 0.201 | | 0.134 | | 0.136 | |

| Panel B | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lending Dynamics: Indirect Climate Exposure | | | | | | | | | |
| | (1) | (2) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Disaster Event | Size | | Spreads | | Maturity | | Covenants | | Collaterals | |
| | Direct | Indirect | Direct | Indirect | Direct | Indirect | Direct | Indirect | Direct | Indirect |
| t0 | 0.110 | 0.000 | 0.756*** | 0.034 | 0.126 | 0.036 | -0.115 | 0.011 | 0.036 | 0.007 |
| | (0.189) | (0.035) | (0.262) | (0.059) | (0.164) | (0.035) | (0.099) | (0.018) | (0.084) | (0.015) |
| t1 | 0.256 | 0.046 | 1.650*** | -0.041 | 0.255 | 0.070 | -0.224 | 0.009 | 0.041 | 0.009 |
| | (0.356) | (0.046) | (0.491) | (0.071) | (0.305) | (0.043) | (0.186) | (0.024) | (0.158) | (0.021) |
| t3 | 0.118 | 0.128* | 0.523 | -0.170 | 0.113 | 0.185*** | -0.153 | 0.007 | 0.187 | 0.008 |
| | (0.363) | (0.074) | (0.574) | (0.109) | (0.312) | (0.066) | (0.190) | (0.039) | (0.161) | (0.033) |
| t6 | 0.463 | 0.015 | 0.975 | -0.212 | 0.309 | 0.235*** | -0.267 | 0.013 | 0.234 | 0.026 |
| | (0.615) | (0.102) | (0.972) | (0.147) | (0.528) | (0.090) | (0.322) | (0.053) | (0.274) | (0.045) |
| t9 | 1.258 | -0.124 | -0.103 | -0.263 | 0.664 | 0.128 | -0.399 | -0.001 | 0.125 | 0.024 |
| | (0.769) | (0.128) | (1.182) | (0.184) | (0.660) | (0.113) | (0.403) | (0.067) | (0.343) | (0.057) |
| t12 | 1.744** | -0.028 | -1.075 | -0.502** | 1.050 | 0.117 | -0.664* | -0.057 | 0.455 | 0.034 |
| | (0.763) | (0.147) | (1.126) | (0.212) | (0.655) | (0.129) | (0.400) | (0.077) | (0.340) | (0.065) |
| t18 | 2.292** | 0.006 | -0.278 | -0.829*** | 1.300 | 0.210 | -0.566 | -0.006 | 0.987** | 0.146* |
| | (1.007) | (0.186) | (1.483) | (0.269) | (0.864) | (0.164) | (0.527) | (0.098) | (0.448) | (0.083) |
| t24 | 1.403 | 0.111 | -2.607 | -1.119*** | 0.989 | 0.342* | -1.083* | 0.012 | 0.770 | 0.185* |
| | (1.149) | (0.218) | (1.667) | (0.316) | (0.986) | (0.192) | (0.602) | (0.114) | (0.512) | (0.097) |
| BankFE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Loan Purpose FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Loan Type FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Firm FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Obs. | 12729 | | 10802 | | 12092 | | 12730 | | 12730 | |
| $R^2$ | 0.837 | | 0.760 | | 0.523 | | 0.573 | | 0.688 | |

To investigate whether banks are reallocating credit from unaffected areas to meet the higher demand in post-disaster affected areas, I further estimate Equation 5 and present the results in Table 6.

At the state-level (Panel A), financial institutions reduce both the total number and volume of loans in unaffected areas, particularly in the short run. Additionally, banks lower interest rates in unaffected regions, signaling a reduced perception of risk. This trend is persistent over time until t6 (0.082***), at which point banks reassess the increased risk and long-term outlook, leading to a reversal of the trend and a positive shift in spreads.

To further isolate the effect of reallocation, Panel B evidence loan-level results, controlling for potential noise arising from firm and loan characteristics. The negative and statistically coefficient for loan volumes in unaffected areas, alongside with the positive coefficients for the affected areas in the long run, suggest that banks are reallocating credit - potentially to support post-disaster affected borrowers who have "survived" the immediate shock and require additional financing. These findings, once again, align with the previous results presented in Table 3. Moreover, the effects remain consistent with those observed at state-level, further reinforcing the reallocation effect by Cortés and Strahan et al. (2017). Additionally, immediately after the disaster t0 (-0.159***), banks significantly reduce interest rates, indicating a temporarily reduction in borrowing costs for non-affected firms, as they are perceived as low-risk borrowers. This adjustment likely reflects a reassessment of borrower risk profiles and increased competition among banks for these "safe borrowers", driving spreads downwards. However, this effect does not persist, as the results remain statistically insignificant at later points. Additionally, banks also adjust loan terms in non-affected areas by consistently shortening maturities throughout the post-disaster period. The results indicate a significant decline in loan maturity, starting from t0 (-0.027**) and continuing until t24. This persistent decrease, also observed at state-level, suggests that banks prioritize short-term lending to maintain liquidity and flexibility, particularly during periods of higher uncertainty. By shortening maturity, banks preserve the ability to reallocate funds as needed, especially if credit demand surges in disaster-affected areas. In addition, the evidence on collaterals requirements aligns with the maturity results on loan-level, as loans with shorter maturities tend to have fewer collateral requirements, reflecting the liquidity-focused nature of the credit extended. In disaster-affected areas, financial institutions often extend larger loan amounts at lower interest rates, playing a critical role in facilitating post-disaster recovery and boosting local economy (Cortés, 2014). Such favorable lending conditions are likely influenced by government guarantees, regulatory incentives or borrower resilience. Related loan support programs can help reduce the perceived risk for financial institutions and encourage the flow of credit. Conversely, for firms operating in unaffected regions, banks reduce interest rates, loosen collaterals requirements and shorten maturity to provide flexibility. This behavior can be attributed to the need to support affected firms, leading banks to reallocate credit towards areas with higher demand, while maintaining liquidity and flexibility, as highlighted by Cortés and Strahan et al. (2017). The findings from complementary analysis at both levels of aggregation show that the reduction in credit supply is persistent across both the intensive and extensive margins, demonstrating that banks indeed reallocate credit towards areas with higher demand - both directly and indirectly affected regions - while maintaining flexibility for liquidity needs by shortening maturities

***Table 5 Lending to Unaffected Areas***

This table presents the results on unaffected areas, that includes a dummy variable that is equal to one if the firm's is headquartered in an unaffected state and zero if it is located in an affected state, as a function of the temporal perspective from the disaster-hit moment until the accumulated previous 24 months on total loss scaled by state GDP. Panel A reports the results on state-level and Panel B on loan-level. All columns in Panel A include macroeconomic controls and incorporate Bank FE. All columns in Panel B include macroeconomic and firm-specific controls and incorporate Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01

Panel A

| | Lending Dynamics: Unaffected States | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Disaster Event | Number of Loans | | Size | | Spreads | | Maturity | | Covenants | | Collaterals | |
| | AF | UN | AF | UN | AF | UN | AF | UN | AF | UN | AF | UN |
| t0 | -3.817*** | -0.881*** | -1.131*** | -0.252*** | 0.831*** | -0.145*** | 0.202** | -0.048*** | -0.132** | 0.027** | 0.109 | -0.002 |
| | (1.187) | (0.103) | (0.299) | (0.026) | (0.235) | (0.021) | (0.103) | (0.009) | (0.067) | (0.006) | (0.068) | (0.006) |
| t1 | -6.457*** | -0.941*** | -1.785*** | -0.281*** | 1.727*** | -0.061*** | 0.301 | -0.058*** | -0.282** | 0.028** | 0.179 | 0.004 |
| | (2.233) | (0.098) | (0.563) | (0.025) | (0.443) | (0.020) | (0.193) | (0.008) | (0.126) | (0.006) | (0.128) | (0.006) |
| t3 | -4.788** | -0.295*** | -1.623*** | -0.267*** | 1.353*** | -0.016 | 0.241 | -0.060*** | -0.005 | 0.028** | 0.284** | 0.014** |
| | (2.294) | (0.102) | (0.577) | (0.026) | (0.523) | (0.020) | (0.198) | (0.009) | (0.130) | (0.006) | (0.131) | (0.006) |
| t6 | -7.690** | -0.415*** | -2.519*** | -0.358*** | 2.742*** | 0.082*** | 0.432 | -0.092*** | -0.112 | 0.030** | 0.433* | 0.016** |
| | (3.886) | (0.121) | (0.977) | (0.030) | (0.877) | (0.024) | (0.335) | (0.010) | (0.219) | (0.007) | (0.222) | (0.007) |
| t9 | -7.296 | 0.010 | -2.635** | -0.534*** | 3.057*** | 0.150*** | 0.733* | -0.162*** | -0.289 | 0.021** | 0.430 | -0.007 |
| | (4.840) | (0.162) | (1.215) | (0.041) | (1.053) | (0.032) | (0.416) | (0.014) | (0.273) | (0.009) | (0.276) | (0.009) |
| t12 | -8.123** | 0.162 | -1.424 | -0.639*** | 1.280 | 0.172*** | 0.607* | -0.207*** | -0.451* | 0.027** | 0.692** | -0.036** |
| | (4.119) | (0.188) | (1.033) | (0.047) | (0.845) | (0.037) | (0.354) | (0.016) | (0.233) | (0.011) | (0.235) | (0.011) |
| t18 | -9.128* | 1.273*** | -1.857 | -0.829*** | 3.105*** | 0.234*** | 0.985** | -0.228*** | -0.399 | 0.040** | 1.272** | 0.024* |
| | (5.426) | (0.245) | (1.363) | (0.062) | (1.106) | (0.049) | (0.467) | (0.021) | (0.307) | (0.014) | (0.309) | (0.014) |
| t24 | -11.660** | -0.472 | -3.084** | -1.122*** | 3.765*** | 0.273*** | 1.002** | -0.240*** | -1.009** | 0.065** | 1.234** | 0.116** |
| | (5.926) | (0.321) | (1.486) | (0.081) | (1.195) | (0.064) | (0.511) | (0.028) | (0.335) | (0.018) | (0.337) | (0.018) |
| BankFE | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Obs. | 14153 | | 14153 | | 13803 | | 14056 | | 14153 | | 14153 | |
| $R^2$ | 0.195 | | 0.190 | | 0.207 | | 0.203 | | 0.135 | | 0.132 | |

| Panel B | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lending Dynamics: Unaffected States | | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Disaster Event | Size | | Spreads | | Maturity | | Covenants | | Collaterals | |
| | AF | UN | AF | UN | AF | UN | AF | UN | AF | UN |
| t0 | -0.028 | -0.079*** | 0.570** | -0.159*** | 0.162 | -0.027* | -0.095 | 0.015 | 0.043 | -0.005 |
| | (0.216) | (0.019) | (0.281) | (0.026) | (0.157) | (0.016) | (0.096) | (0.010) | (0.082) | (0.008) |
| t1 | 0.255 | -0.065*** | 1.577*** | -0.029 | 0.307 | -0.038** | -0.197 | 0.019** | 0.050 | -0.003 |
| | (0.351) | (0.018) | (0.484) | (0.026) | (0.301) | (0.016) | (0.184) | (0.009) | (0.157) | (0.008) |
| t3 | 0.194 | -0.074*** | 0.308 | -0.019 | 0.265 | -0.056*** | -0.142 | 0.004 | 0.190 | -0.006 |
| | (0.354) | (0.019) | (0.560) | (0.027) | (0.304) | (0.016) | (0.185) | (0.010) | (0.158) | (0.008) |
| t6 | 0.389 | -0.078*** | 0.686 | -0.023 | 0.502 | -0.063*** | -0.249 | 0.003 | 0.234 | -0.025** |
| | (0.604) | (0.023) | (0.955) | (0.033) | (0.519) | (0.020) | (0.317) | (0.012) | (0.269) | (0.010) |
| t9 | 1.068 | -0.158*** | -0.446 | -0.062 | 0.785 | -0.097*** | -0.405 | -0.012 | 0.134 | -0.064*** |
| | (0.754) | (0.032) | (1.160) | (0.047) | (0.647) | (0.028) | (0.396) | (0.017) | (0.336) | (0.014) |
| t12 | 1.685** | -0.186*** | -1.706 | -0.083 | 1.180* | -0.086** | -0.734* | -0.015 | 0.485 | -0.082*** |
| | (0.742) | (0.039) | (1.096) | (0.056) | (0.637) | (0.034) | (0.389) | (0.020) | (0.331) | (0.017) |
| t18 | 2.306** | -0.269*** | -1.281 | 0.035 | 1.550* | -0.085* | -0.573 | -0.006 | 1.159*** | -0.034 |
| | (0.981) | (0.054) | (1.447) | (0.080) | (0.842) | (0.048) | (0.515) | (0.029) | (0.437) | (0.024) |
| t24 | 1.544 | -0.252*** | -3.865** | 0.106 | 1.372 | -0.135** | -1.073* | 0.042 | 0.970* | 0.033 |
| | (1.123) | (0.073) | (1.631) | (0.107) | (0.963) | (0.064) | (0.589) | (0.038) | (0.500) | (0.033) |
| BankFE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Loan Purpose FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Loan Type FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Firm FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| Obs. | 12729 | | 10802 | | 12092 | | 12730 | | 12730 | |
| $R^2$ | 0.837 | | 0.760 | | 0.523 | | 0.573 | | 0.688 | |

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## 4.3. Selection Channels

To examine whether banks prioritize creditworthy firms for post-disaster rebuilding, I analyze Table 6, splitting the sample using Altman's Z-Score. Additionally, I assess two other lending channels by segmenting firms based on profitability and size. All tables referenced, including Tables 7, 8, and 9, are presented in the Appendix.

Natural disasters cause financial disruptions, prompting banks to adjust lending strategies to balance risk exposure and economic recovery. The findings indicate that banks initially rely on pricing mechanisms to mitigate disaster risk. This effect is particularly strong for high-quality and profitable firms, as banks impose stricter conditions on them post-disaster. However, over time, banks expand credit to firms that either survive and demonstrate resilience or benefit from insurance and government support.

In the short run, loan sizes show no significant changes, suggesting banks rely primarily on interest rate adjustments. Borrowing costs rise significantly, confirming that banks use spreads to manage climate exposure immediately after disasters. High-profit and high-quality firms help meet liquidity needs, enabling banks to offer lower spreads to riskier firms. Large firms face an initial increase in spreads at t0 (5.967**) and t6 (6.064*), likely due to greater asset exposure. Conversely, low-quality firms experience declining spreads over time, particularly from t3, with the largest reductions at t9 (-5.442***) and t24 (-5.932**). This suggests banks lower borrowing costs for riskier firms as part of a recovery strategy, driven partially by survivorship bias. High-quality firms consistently face higher spreads in the early months but see declines by t24 (-7.428**), indicating banks initially impose higher borrowing costs on stronger firms to support weaker borrowers.

As market conditions stabilize, loan sizes increase significantly for both small and large firms, particularly from t12 to t24. High-profit firms show a steady rise in loan amounts, while low-profit firms do not experience sustained increases. Loan maturity also exhibits a significant increase for large firms, particularly at t12 (7.254**), t18 (9.603**), and t24 (8.885**), suggesting that banks extend repayment periods for large firms due to their higher credit supply. Loan covenants, which impose contractual restrictions on borrowers, become significantly loosened for both small and large firms post-disaster. The effect is strongest for large firms at t3 (-2.208*), implying that banks impose looser monitoring on financially stable borrowers. However, small firms also face fewer covenant restrictions, particularly at t9 (-0.856*) and t24 (-1.264*), possibly due to the need for greater liquidity support in smaller businesses. Collateral requirements follow a different pattern. Small firms face a significant increase in collateral demand at t3, t6, t12, t18, and t24, with the strongest effect at t18 (2.126***), suggesting that banks require additional security when extending credit to smaller businesses post-disaster. Low-quality firms also face higher collateral burdens at t18 (1.583*), reinforcing their classification as riskier borrowers. Surprisingly, high-profit firms experience a substantial increase in collateral requirements at t9 (1.776*) and t18 (2.490***), with a peak at t24 (2.851***), suggesting that banks take a precautionary approach even toward financially stronger firms in uncertain periods.

The results suggest that banks first rely on pricing mechanisms post-disaster but later adjust loan sizes as recovery unfolds. Initially, they raise borrowing costs for large high-quality and profitable firms to subsidize lower rates for weaker borrowers. Over time, this strategy reverses, reducing spreads for stronger firms and expanding credit to surviving businesses. The shift in lending behavior suggests that, rather than outright risk aversion, banks employ a strategic approach, balancing financial stability with economic recovery. Existing literature, such as Goss and Roberts et al. (2021), also suggests that banks actively screen and prioritize high-quality firms in the post-disaster period, yet this study finds a deviation from traditional quality selection mechanisms. Rather than exclusively favoring strong firms, banks initially adjust spreads in favor of financially weaker firms, ensuring credit accessibility before reallocating resources toward stronger firms. Similar trends at the state level reinforce the notion that banks provide post-recovery support to lower-quality firms.

## 4.4. Economic Channels

Government assistance programs, such as SBA and FEMA, can incentivize banks to offer favorable lending terms in high-risk areas to support post-disaster recovery. Financial institutions typically raise interest rates, shorten maturities, and tighten covenants to manage uncertainty surrounding borrowers' repayment capacity in high-risk environments (Cortés et al., 2014; Javadi and Masum, 2021). However, regulatory pressure and government support may counteract these measures, leading banks to offer more favorable loan terms to high-risk borrowers. Government guarantees can reduce lender uncertainty, making government-backed borrowers appear lower risk

(Manove, 2000). Disaster relief programs such as SBA and FEMA loans can mitigate the adverse effects of climate-related financial risks and improve credit access for affected firms.

To explicitly examine whether government incentives influence the results I analyze how FEMA disaster loans - aggregated at the state-month and year level as a proxy for government intervention - interact with direct climate exposure to shape lending conditions. The primary variable of interest is the interaction term (Exposure × DisasterLoans), which indicates whether government support moderates the relationship between disaster exposure and lending terms.

Results show that in states receiving higher FEMA loans, banks raise interest rates more than in disaster-affected states without government support. Banks may interpret disaster aid as a signal of ongoing financial vulnerability. Additionally, FEMA loans may not fully restore stability, prompting banks to increase spreads to manage risk. Another potential mechanism is the crowding-out effect, where government loans reduce reliance on private credit, leading to lower loan demand and higher spreads for remaining borrowers. However, due to the aggregation of data at state-level, this study does not capture the specific government support provided to individual firms. Ideally, a comparison between firms that received government assistance and those that did not, despite being affected by the same disaster, would provide more granular insights. The lack of firm-level variation in the current state-level data may limit the precision of the conclusions drawn from this analysis.

## 4.5. Robustness Checks

To assess the robustness of the main results, I investigate whether past natural disasters can predict future disaster occurrences. Specifically, I employ a fixed effects regression model to analyze the relationship between the materialization of natural disaster and the associate risk. The model is built at a state-month level and estimates the probability of future occurrence based on previous ones. The dependent variable is a binary indicator, equal to 1 if a disaster occurs in month t. The key independent variables are lagged disaster dummies, capturing disaster occurrences from 1 to 24 months prior. Additionally, I incorporate macroeconomic controls to account for broader economic conditions that may influence disaster reporting or response. The model further includes state fixed effects to eliminate bias arising from variations across states.

The fixed effects regression model is specified as follows:

$$\text{Disaster}_{t} = \Sigma_{1}^{24} ( \alpha \, \text{Disaster}_{t-n} ) + \gamma \, \text{Macroeconomic controls}_{t-1} + \text{State FE} + \varepsilon_{s,t} \tag{7}$$

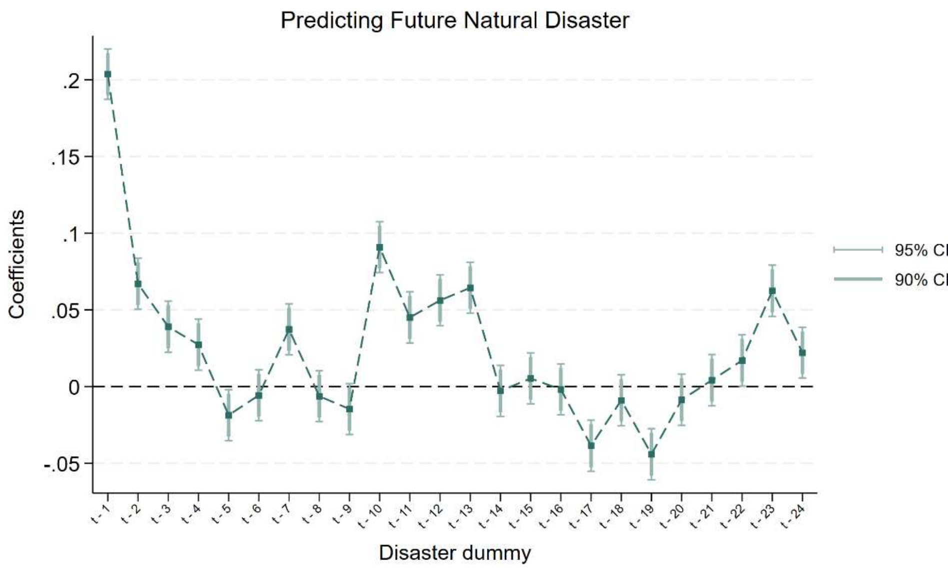



***Figure 1 Predicting Future Natural Disaster***

This figure plots the estimated coefficients from the fixed effects model regression assessing whether past natural disasters predict future disaster occurrences at the state-month level. The dependent variable is a binary indicator equals to 1 if a natural disaster occurs in month t. The independent variables are lagged disaster dummies measured from 1month before until 24 months before t. The model controls macroeconomic state-level conditions. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01.

The results show that past natural disasters are strong predictors of future occurrences, particularly in the short term. The 1-month lag has the highest coefficient (0.204, p<0.01) and remains significant throughout the 4-month lag (0.027, p<0.01), indicating that a disaster significantly increases the probability of another event in the following months. This can be attributed to recurring environmental conditions, cascading effects, and lingering structural vulnerabilities, though the impact diminishes over time. However, significance re-emerges at t-10 to t-13 months (0.091 to 0.064, p<0.01), suggesting seasonal patterns in disaster recurrence. This aligns with hazard-specific seasonality, reinforcing the importance of incorporating historical disaster patterns into risk assessment and climate adaptation strategies. Figures 4 to 10 in Appendix plots the different types of hazards. The model's R-square statistics (=0.191) further supports the robustness of these findings, confirming that disaster occurrence is influenced not only by immediate past events but also by broader environmental and climatic cycles. However, the relatively low Rsquared values indicate the possibility of omitted variables that could explain additional variation in disaster occurrences.

## 5. Conclusion

This study provides a comprehensive analysis of how banks adjust lending practices in response to climate-related disasters, exploring the evolving dynamics of credit reallocation and portfolio rebalancing. By examining both aggregate state-level and loan-level dynamics, the study highlights the interplay and complementary nature of these two dimensions: 1) the broader macro-level lending behavior, and 2) the granular loan-level lending dynamics.

The state-level results highlight the extensive margin effects, where banks reduce the total number and volume of loans in states directly exposed to climate-related disasters. This contraction reflects a broad-scale adjustment in credit availability, as financial institutions limit lending and charge higher interest rates to borrowers headquartered in affected states. Directly exposed states consistently experience declines in loan amounts and volume, along with rising interest rates. Additionally, financial institutions respond to spillover effects, such as supply chain disruptions and cascading impacts, by expanding credit availability in neighboring states. While interest rates remain unchanged, the increase in loan volume suggests that banks are responding to higher credit demand in neighboring disaster-affected states while also seeking to mitigate economic disruptions and support long-term client relationships. Comparing affected and unaffected regions, the findings reveal that credit is reallocated to high-demand areas, leading to declining loan volume and size in unaffected states. Notably, interest rates drop post-disaster, indicating that banks adjust pricing to reflect the lower risk profile of these regions. Shorter maturities serve as a precautionary measure to preserve liquidity and offset increased lending to high-risk areas. These results demonstrate how banks dynamically adjust credit allocation following disasters, balancing risk mitigation, liquidity management, and economic recovery.

At the loan level, the effects vary as the analysis focuses on the intensive margin, examining how banks adjust loan terms for firms that secure new credit post-disaster. After controlling for firm and loan characteristics, the findings indicate that banks do not immediately adjust non-pricing loan mechanisms but instead increase interest rates sharply, reflecting heightened uncertainty. Over time, as economic conditions stabilize and insurance interventions take effect, banks gradually lower interest rates and expand credit supply, favoring firms that demonstrate resilience or benefit from institutional support. Initially, banks rely on pricing mechanisms to mitigate post-disaster risk, raising interest rates to compensate for increased uncertainty. As time progresses, lending conditions shift as banks identify and prioritize firms that have successfully navigated the crisis. The analysis of direct vs. indirect exposure further reveals distinct patterns. In the short run, directly affected firms face higher interest rates, while credit supply remains uncertain. However, in the long run, banks extend more credit to these firms, likely due to their increased need for support and survivorship bias. For indirectly exposed firms, interest rates initially remain stable but later turn negative, indicating that banks may perceive them as lower risk. However, this trend is accompanied by stricter collateral requirements, ensuring closer borrower monitoring. For unaffected regions, loan-level data consistently captures a significant reduction in loan volume and maturity, suggesting that banks reallocate credit toward higher-demand regions while preserving liquidity. By shortening maturities, banks maintain financial flexibility in uncertain environments. These findings confirm the portfolio rebalancing and credit reallocation effects, aligning with Cortés and Strahan et al. (2017). Rather than exhibiting outright risk aversion, banks dynamically adjust their strategies, shifting from pricing-based risk management in the short term to selective credit expansion as post-disaster conditions stabilize.

By analyzing selection channels, I find evidence that financial institutions support riskier borrowers' post-disaster. In the short run, banks use pricing mechanisms to mitigate risks, gradually shifting toward adjusting loan size as recovery progresses. Initially, they increase borrowing costs for large, high-quality, and profitable firms to subsidize lower rates for financially weaker ones, ensuring credit availability. Over time, this reverses as spreads decline for stronger firms and credit expands for disaster survivors. This shift reflects a strategic balance between stability and recovery. The long-term effects stem partly from survivorship bias, as firms that endure the disaster may transition toward financial stability. Additionally, banks provide more favorable pricing to low-quality firms, diverging from prior research that suggests they prioritize high-quality borrowers (Goss & Roberts, 2011; Bolton & Kacperczyk, 2022b).

Despite the negative impact of disasters, government programs like SBA and FEMA encourage favorable lending terms in high-risk areas. However, financial institutions often raise interest rates, particularly in regions with higher FEMA assistance, possibly due to perceived borrower vulnerability. Nevertheless, the approximation is not precise, making it inconclusive whether government support directly leads to higher interest rates.

The results highlight that past natural disasters are strong predictors of future events, particularly in the short term, with significance extending for several months. This suggests that recurring environmental conditions and structural vulnerabilities contribute to disaster recurrence, with patterns aligning with seasonal cycles. The findings emphasize the importance of incorporating historical disaster data into future risk assessments and climate adaptation strategies.

# 6. Appendix

***Table 6 Variables Description***

| Variable | Definition | Source |
|---|---|---|
| *Climate Exposure* | | |
| Property Damage | Property loss ( in millions) due to climate exposure (Adjusted for 2023) aggregated on state-level | SHELDUS |
| Crop Damage | Crop loss (in millions) due to climate exposure (Adjusted for 2023 ) aggregated on state-level | SHELDUS |
| Total Damage | Total damage (crop + property) acumulated over the t0 - t24 window periods | SHELDUS |
| Direct Exposure | Total damaged scaled by GDP per state | $\text{Climate } Exposure_m = \left(\frac{Damage\ Cum_m}{GDP_m}\right)$ |
| Indirect Exposure | Aggregated risk of the neighboring states (distance between states = 0) | |
| *Loan features* | | |
| Log (Deal amount) | Total Deal Amount; log transformed | Refinitive LoanConnector DealScan |
| Spread | all drawn annulayy over LIBOR in percentage points | Refinitive LoanConnector DealScan |
| Loan Duration | Maturity of loans in months; log transformed | Refinitive LoanConnector DealScan |
| Covenants | Dummy variable (=1 if loan have financial ou general govenants and =0 if not) | Refinitive LoanConnector DealScan |
| *Macroeconomic Controls* | | |
| GDP by state | Gross domestic (in millions) product by state, per year | U.S Census Bureau |
| %unemployment | Growth of unemployment over the 6-,12-,24-month rw | U.S Census Bureau |
| %inflation | Growth of inflation over the 6-,12-,24-month rw | U.S Census Bureau |
| %gdp | Growth of gdp over the 6-,12-,24-month rw | U.S Census Bureau |
| *Firms Controls* | | |
| Log (Assets) | Total Asset; log transformed | Compustat; log(at) |
| Leverage | Total debt over Asset; log transformed | Compustat; log(dtt/at) |
| Book-to-market | Book-to-market value | Compustat; (prcc_f x csho + lit)/(ceq + lt) |
| ROA | Return on Assets | Compustat; ni/at |
| *Loan Type FE* | | |
| TERM | Loan type (=1, if type of borrowing is a term loan) | Refinitive LoanConnector DealScan |
| LINE | Loan type (=2, if type of borrowing if a line loan) | Refinitive LoanConnector DealScan |
| LETTER OF CREDIT | Loan type (=2, if type of borrowing is a letter-of-credit) | Refinitive LoanConnector DealScan |
| 364-DAY FACILITY | Loan type (=2, if the type of borrowing is a 364-day facility) | Refinitive LoanConnector DealScan |

| | | |
|---|---|---|
| *Disaster Loans* | | |
| Disaster Loans | Disaster Loan amount  (in millions) aggregaed on state and month frequency | FEMA |
| DS_Dummy | (=1 In the presence of a disaster loan) | FEMA |
| *Loan Purpose* | | |
| CORP | Loan purpose (=1, if the purpose is to spend in acquisitions, buyout, merger, spinoff, takeover) | Refinitive LoanConnector DealScan |
| GENEREL PURPOSE | Loan purpose (=2, if the purpose is to spend in general purpose) | Refinitive LoanConnector DealScan |
| FINANCIAL | Loan purpose (=3, if the purpose is to spend in financial purposes) | Refinitive LoanConnector DealScan |
| OTHER | Loan purpose (=4, if the purpose is to spend in others) | Refinitive LoanConnector DealScan |

***Table 7 The Role of Creditworthiness in Climate-Exposed Lending***

This table presents two sub-samples grouped according to low-quality firms and high-quality firms. The sample is split using Altman's Z-score. All columns include macroeconomic and firm controls. All columns include Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01

| | *Lending Dynamics Over Creditworthiness* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | *Disaster Event Window* | | | | | | | |
| | *t0* | *t1* | *t3* | *t6* | *t9* | *t12* | *t18* | *t24* |
| | Size | | | | | | | |
| *Low Quality* | 0.825 | 2.211 | 1.203 | 1.914 | 2.486* | 2.591** | 2.916** | 2.414 |
| | (1.448) | (1.589) | (0.934) | (1.367) | (1.337) | (1.235) | (1.481) | (1.820) |
| | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) |
| *High Quality* | -0.180 | 0.221 | 0.474 | 0.437 | 1.385 | 2.551 | 3.442 | -0.878 |
| | (0.579) | (0.797) | (1.205) | (1.709) | (2.197) | (2.542) | (3.248) | (2.300) |
| | (5787) | (5787) | (5787) | (5787) | (5787) | (5787) | (5787) | (5787) |
| | Spread | | | | | | | |
| *Low Quality* | -2.577 | -2.296 | -2.009** | -2.955* | -4.789*** | -5.442*** | -4.663** | -5.932** |
| | (2.702) | (2.484) | (0.948) | (1.621) | (1.683) | (1.854) | (2.258) | (2.765) |
| | (4814) | (4814) | (4814) | (4814) | (4814) | (4814) | (4814) | (4814) |
| *High Quality* | 0.884*** | 1.796*** | 3.021*** | 4.581** | 6.322** | -2.047 | -0.529 | -7.428** |
| | (0.292) | (0.570) | (1.102) | (1.810) | (2.457) | (3.365) | (4.288) | (2.973) |
| | (4968) | (4968) | (4968) | (4968) | (4968) | (4968) | (4968) | (4968) |
| | Maturity | | | | | | | |
| *Low Quality* | 1.568 | 1.508 | 1.108 | 1.536 | 1.514 | 1.095 | 1.487 | 1.444 |
| | (1.439) | (1.480) | (0.846) | (1.235) | (1.205) | (1.111) | (1.335) | (1.641) |
| | (5450) | (5450) | (5450) | (5450) | (5450) | (5450) | (5450) | (5450) |
| *High Quality* | 0.406 | 0.645 | 0.888 | 1.221 | 1.161 | 2.354 | 3.506 | 0.939 |
| | (0.511) | (0.699) | (1.057) | (1.497) | (1.929) | (2.275) | (2.901) | (2.020) |
| | (5552) | (5552) | (5552) | (5552) | (5552) | (5552) | (5552) | (5552) |
| | Covenants | | | | | | | |
| *Low Quality* | -0.769 | -0.290 | 0.189 | 0.422 | -0.323 | -0.865 | -0.120 | -1.034 |
| | (0.781) | (0.857) | (0.504) | (0.737) | (0.721) | (0.666) | (0.799) | (0.981) |
| | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) |
| *High Quality* | -0.007 | -0.195 | -0.666 | -1.077 | -0.950 | -0.071 | -0.318 | -0.815 |
| | (0.300) | (0.413) | (0.624) | (0.885) | (1.138) | (1.318) | (1.684) | (1.192) |
| | (5788) | (5788) | (5788) | (5788) | (5788) | (5788) | (5788) | (5788) |
| | Collateral | | | | | | | |
| *Low Quality* | -0.776 | -1.181 | 0.409 | 0.680 | 0.062 | 0.421 | 1.583** | 1.319 |
| | (0.661) | (0.726) | (0.427) | (0.624) | (0.611) | (0.564) | (0.677) | (0.831) |
| | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) | (5811) |
| *High Quality* | 0.172 | 0.192 | 0.372 | -0.201 | -0.200 | -0.552 | -0.661 | 0.093 |
| | (0.252) | (0.347) | (0.524) | (0.743) | (0.956) | (1.106) | (1.413) | (1.000) |
| | (5788) | (5788) | (5788) | (5788) | (5788) | (5788) | (5788) | (5788) |

***Table 8 The Role of Firm Size in Climate-Exposed Lending***

This table presents two sub-samples, categorizing firms as small or large based on their size. The sample is split using Log (Assets). All columns include macroeconomic and firm controls. All columns include Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01

| | *Lending Dynamics Over Firm Size* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | *Disaster Event Window* | | | | | | | |
| | *t0* | *t1* | *t3* | *t6* | *t9* | *t12* | *t18* | *t24* |
| | Size | | | | | | | |
| *Small* | 0.116 | 0.213 | 0.247 | 0.321 | 0.739 | 1.247* | 1.919* | 1.184 |
| | (0.157) | (0.309) | (0.380) | (0.658) | (0.810) | (0.723) | (0.990) | (1.100) |
| | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) |
| *Large* | -1.797 | 0.694 | -1.069 | 1.609 | 7.165** | 6.307* | 9.930** | 10.400** |
| | (1.719) | (1.477) | (2.192) | (2.751) | (3.057) | (3.419) | (4.245) | (4.927) |
| | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) |
| | Spread | | | | | | | |
| *Small* | 0.383 | 0.917 | 0.948 | 1.586 | -0.697 | -1.982 | -1.791 | -4.541** |
| | (0.285) | (0.564) | (0.905) | (1.566) | (1.764) | (1.426) | (1.947) | (2.106) |
| | (4665) | (4665) | (4665) | (4665) | (4665) | (4665) | (4665) | (4665) |
| *Large* | 5.967** | 1.707 | 4.196 | 6.064* | 4.199 | 6.493 | 8.837 | 5.435 |
| | (2.844) | (1.844) | (2.713) | (3.459) | (3.882) | (4.582) | (5.530) | (6.368) |
| | (5502) | (5502) | (5502) | (5502) | (5502) | (5502) | (5502) | (5502) |
| | Maturity | | | | | | | |
| *Small* | 0.345 | 0.279 | 0.417 | 0.471 | 0.809 | 0.877 | 1.049 | 1.180 |
| | (0.353) | (0.498) | (0.508) | (0.758) | (0.873) | (0.750) | (0.970) | (1.059) |
| | (5230) | (5230) | (5230) | (5230) | (5230) | (5230) | (5230) | (5230) |
| *Large* | 0.789 | 0.525 | 1.009 | 2.498 | 3.804 | 7.254** | 9.603** | 8.885** |
| | (1.685) | (1.429) | (2.042) | (2.527) | (2.821) | (3.140) | (3.884) | (4.529) |
| | (6230) | (6230) | (6230) | (6230) | (6230) | (6230) | (6230) | (6230) |
| | Covenants | | | | | | | |
| *Small* | -0.261 | -0.422 | -0.135 | -0.141 | -0.409 | -0.856* | -0.624 | -1.264* |
| | (0.232) | (0.329) | (0.337) | (0.504) | (0.580) | (0.498) | (0.645) | (0.703) |
| | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) |
| *Large* | -0.047 | -0.675 | -2.208* | -1.407 | -0.605 | -0.781 | -1.037 | -3.160 |
| | (0.983) | (0.835) | (1.187) | (1.468) | (1.620) | (1.805) | (2.230) | (2.593) |
| | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) |
| | Collateral | | | | | | | |
| *Small* | 0.138 | 0.151 | 0.662** | 0.891* | 0.516 | 1.194** | 2.126*** | 1.732** |
| | (0.223) | (0.317) | (0.324) | (0.485) | (0.558) | (0.480) | (0.620) | (0.676) |
| | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) | (5602) |
| *Large* | 0.200 | 0.209 | 0.477 | -0.755 | -0.479 | -0.621 | -1.257 | -2.506 |
| | (0.738) | (0.627) | (0.892) | (1.102) | (1.216) | (1.355) | (1.674) | (1.946) |
| | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) | (6478) |

***Table 9 The Role of Profitability in Climate-Exposed Lending***

This table presents two sub-samples, categorizing firms as low-profitable or high-profitable firms based on their financial performance. The sample is split using ROA. All columns include macroeconomic and firm controls. All columns include Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01

| | *Lending Dynamics Over Profitability* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | *Disaster Event Window* | | | | | | | |
| | *t0* | *t1* | *t3* | *t6* | *t9* | *t12* | *t18* | *t24* |
| | Size | | | | | | | |
| *Low Profitable* | -2.211 | 0.105 | -1.391 | 0.032 | 1.129 | 1.209 | 0.232 | -2.121 |
| | (1.457) | (1.557) | (2.377) | (2.832) | (1.766) | (2.127) | (2.452) | (2.170) |
| | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) |
| *High Profitable* | -0.081 | 0.182 | 0.736 | 1.055 | 2.076 | 3.273* | 3.902* | 4.339* |
| | (0.598) | (0.840) | (0.863) | (1.282) | (1.650) | (1.670) | (2.014) | (2.463) |
| | (5941) | (5941) | (5941) | (5941) | (5941) | (5941) | (5941) | (5941) |
| | Spread | | | | | | | |
| *Low Profitable* | -2.459 | -2.089 | -0.304 | 4.783 | -3.611 | -4.374 | 6.836 | -5.817 |
| | (2.780) | (2.897) | (4.549) | (5.552) | (3.306) | (4.028) | (4.406) | (3.723) |
| | (4382) | (4382) | (4382) | (4382) | (4382) | (4382) | (4382) | (4382) |
| *High Profitable* | 0.924*** | 2.034*** | 1.516** | 2.468** | 3.893** | -0.922 | -1.022 | -1.830 |
| | (0.244) | (0.480) | (0.618) | (1.061) | (1.736) | (1.761) | (2.115) | (2.392) |
| | (5143) | (5143) | (5143) | (5143) | (5143) | (5143) | (5143) | (5143) |
| | Maturity | | | | | | | |
| *Low Profitable* | -0.124 | -0.724 | -0.157 | 0.259 | 0.124 | 0.093 | 0.053 | -0.607 |
| | (1.282) | (1.370) | (2.151) | (2.521) | (1.554) | (1.874) | (2.164) | (1.912) |
| | (5010) | (5010) | (5010) | (5010) | (5010) | (5010) | (5010) | (5010) |
| *High Profitable* | 0.424 | 0.876 | 0.927 | 1.419 | 2.095 | 2.805* | 2.790 | 3.005 |
| | (0.541) | (0.754) | (0.767) | (1.138) | (1.465) | (1.479) | (1.784) | (2.183) |
| | (5720) | (5720) | (5720) | (5720) | (5720) | (5720) | (5720) | (5720) |
| | Covenants | | | | | | | |
| *Low Profitable* | -0.549 | -0.644 | -0.873 | 1.303 | -0.520 | -1.272 | -0.254 | -1.099 |
| | (0.793) | (0.848) | (1.294) | (1.541) | (0.962) | (1.158) | (1.335) | (1.181) |
| | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) |
| *High Profitable* | -0.048 | -0.207 | -0.226 | -0.536 | -0.567 | -1.404 | -0.518 | -1.258 |
| | (0.309) | (0.434) | (0.446) | (0.663) | (0.853) | (0.864) | (1.042) | (1.274) |
| | (5942) | (5942) | (5942) | (5942) | (5942) | (5942) | (5942) | (5942) |
| | Collateral | | | | | | | |
| *Low Profitable* | -0.909 | -0.187 | 1.457 | 1.142 | 0.168 | -0.232 | 1.305 | 0.029 |
| | (0.711) | (0.760) | (1.160) | (1.382) | (0.862) | (1.038) | (1.197) | (1.059) |
| | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) | (5402) |
| *High Profitable* | 0.038 | -0.013 | 0.630* | 0.749 | 0.904 | 1.776*** | 2.490*** | 2.851*** |
| | (0.233) | (0.327) | (0.335) | (0.498) | (0.642) | (0.649) | (0.782) | (0.957) |
| | (5942) | (5942) | (5942) | (5942) | (5942) | (5942) | (5942) | (5942) |

***Table 10 Effects of Disaster-Loans on Lending to Disaster-Prone Areas***

This table presents the effects of disaster-loans on contractual terms – size and spreads. The model includes a dummy variable that is equal to one if the state had support and zero if not, as a function of the temporal perspective from the disaster-hit moment until the accumulated previous 24 months on total loss scaled by state GDP, on loan level. All columns include Firm FE, Bank FE, Loan Type and Loan Purpose FE. Standard errors in parenthesis. * p<0.10 ** p<0.05 *** p<0.01

| | Lending Dynamics: Disaster-Loans | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Disaster Event | Size | | | Spread | | |
| | Climate Exposure | Disaster-Loans | Interaction | Climate Exposure | Disaster-Loans | Interaction |
| t0 | -1.402 | -0.098 | -3.385 | -6.925 | -0.018 | 6.765 |
| | (3.209) | (0.066) | (5.911) | (7.093) | (0.118) | (11.922) |
| t1 | 0.923 | -0.052 | -3.586 | 2.855 | 0.016 | -8.197 |
| | (1.323) | (0.052) | (3.395) | (2.195) | (0.091) | (6.272) |
| t3 | -0.039 | -0.019 | 0.774 | -1.048 | 0.023 | -9.352 |
| | (0.549) | (0.046) | (4.652) | (0.808) | (0.073) | (7.759) |
| t6 | 0.088 | 0.003 | 0.984 | -1.738 | 0.045 | -8.869 |
| | (0.895) | (0.042) | (7.407) | (1.284) | (0.066) | (11.886) |
| t9 | 0.617 | -0.004 | 1.405 | -4.708*** | -0.001 | 11.746*** |
| | (0.889) | (0.038) | (2.421) | (1.510) | (0.059) | (3.491) |
| t12 | 1.501* | -0.006 | 0.615 | -3.938*** | 0.001 | 11.174*** |
| | (0.825) | (0.038) | (2.464) | (1.273) | (0.057) | (3.426) |
| t18 | 2.120** | 0.001 | 0.661 | -2.584 | 0.006 | 14.385*** |
| | (1.041) | (0.037) | (3.465) | (1.571) | (0.056) | (4.809) |
| t24 | 0.988 | 0.002 | 0.478 | -5.429*** | -0.008 | 18.878*** |
| | (1.175) | (0.037) | (4.401) | (1.735) | (0.056) | (6.081) |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 14153 | 14153 | 13803 | 14056 | 12730 | 12730 |
| $R^2$ | 0.210 | 0.213 | 0.206 | 0.204 | 0.573 | 0.688 |

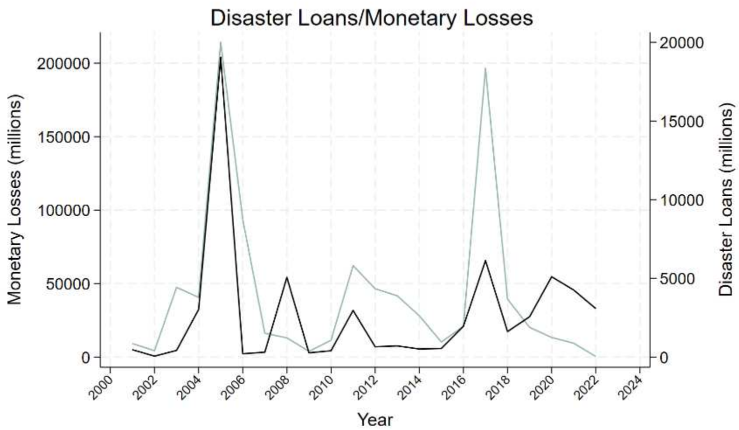
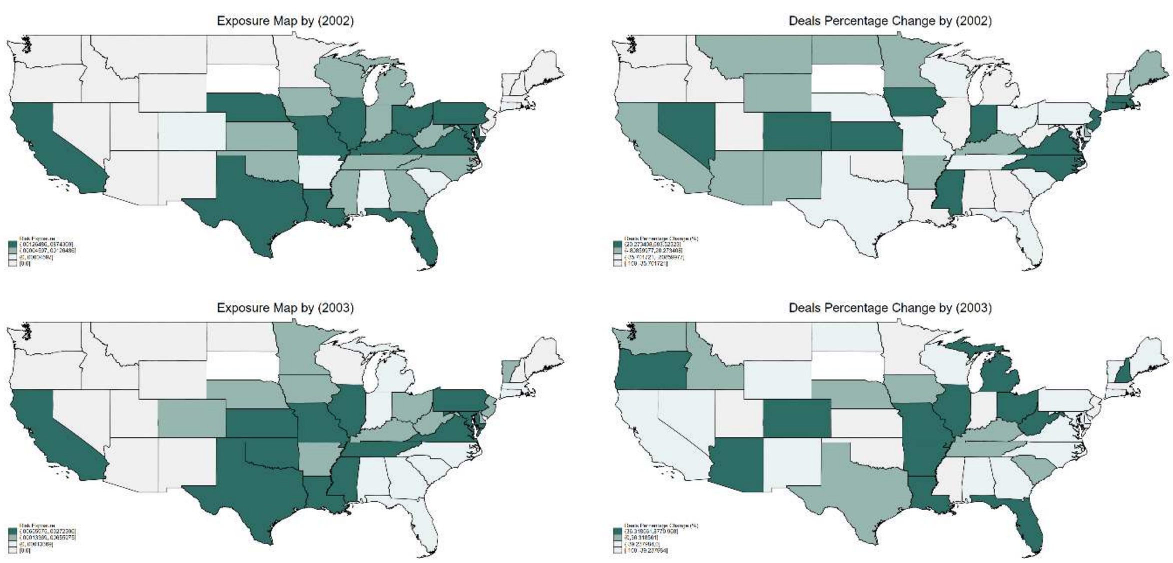
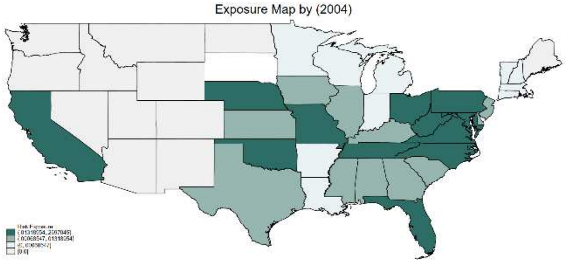



***Figure 2 Disaster Loans and Natural Hazards***

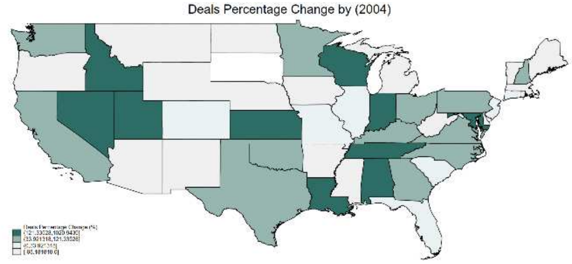
This figure illustrates the relationship between monetary losses from natural hazards (incl. property damage and crop damage) and the volume of disaster-loans disbursed by FEMA (Federal Emergency Management Agency) over the full sample period. Monetary losses (left axis) are reported in millions, while disaster loans amounts (right axis) are also reported in millions.



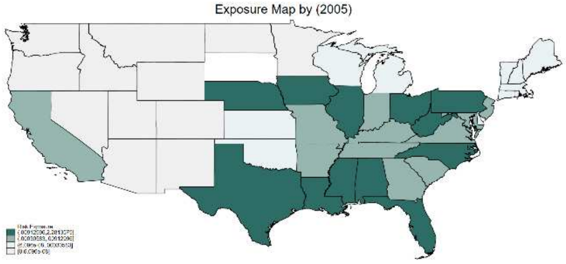
Exposure Map by (2004)



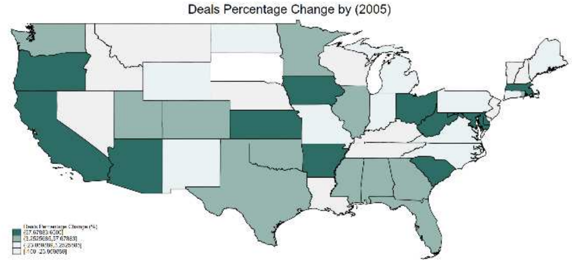
Deals Percentage Change by (2004)



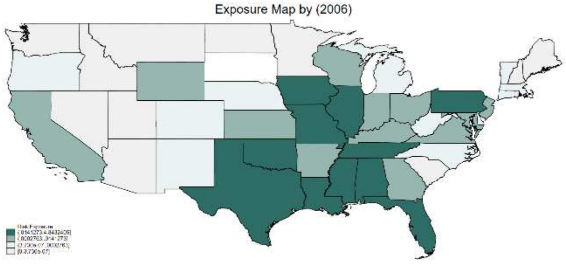
Exposure Map by (2005)



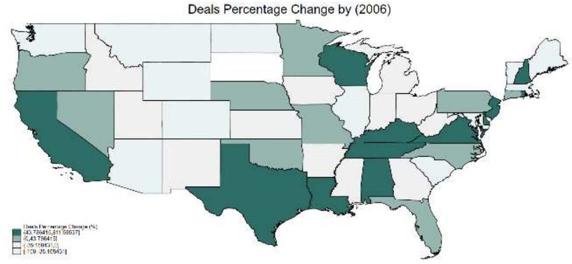
Deals Percentage Change by (2005)



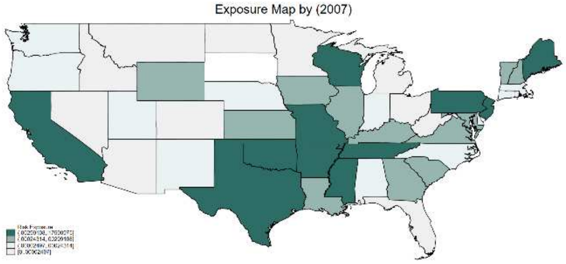
Exposure Map by (2006)



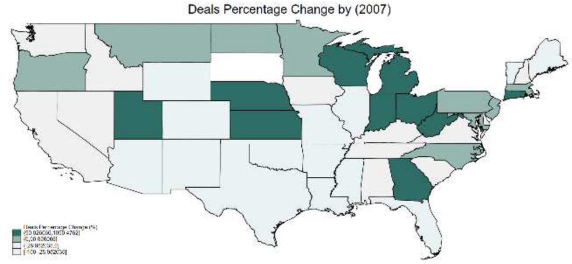
Deals Percentage Change by (2006)



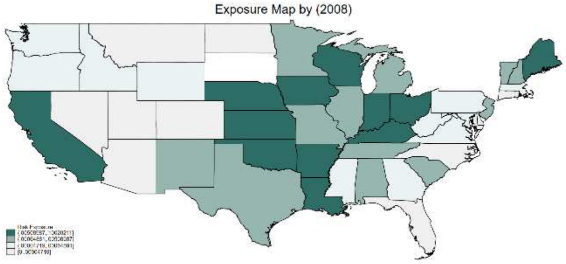
Exposure Map by (2007)



Deals Percentage Change by (2007)



Exposure Map by (2008)



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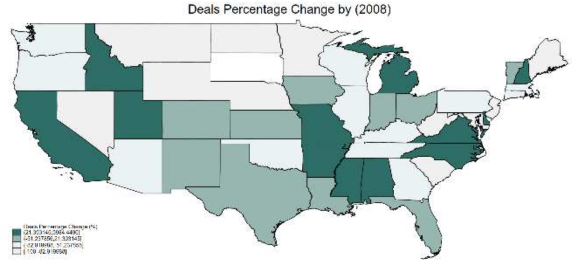
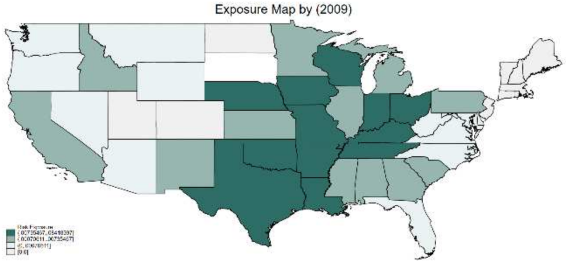
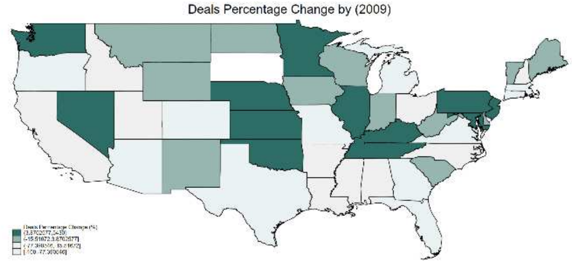


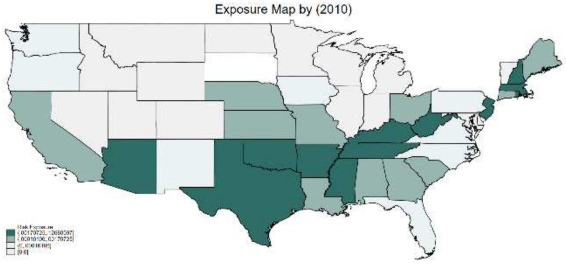
Exposure Map by (2009)



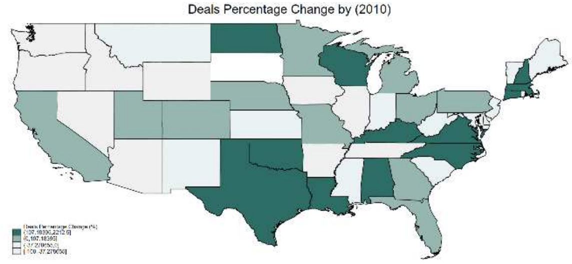
Deals Percentage Change by (2009)



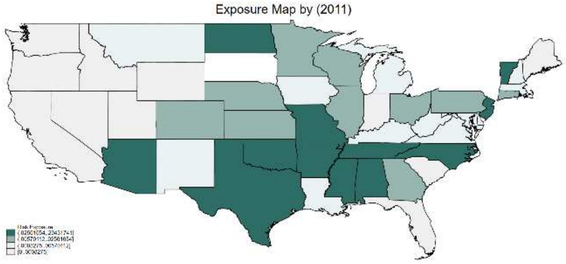
Exposure Map by (2010)



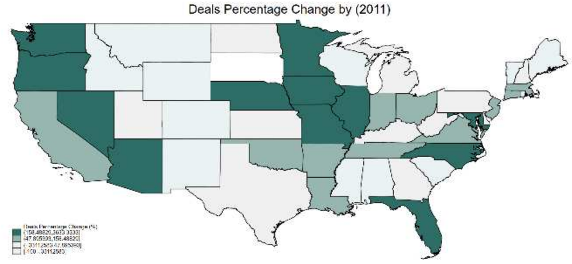
Deals Percentage Change by (2010)



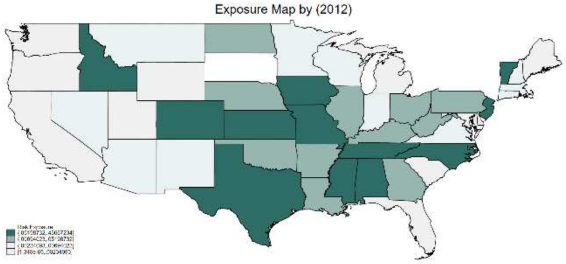
Exposure Map by (2011)



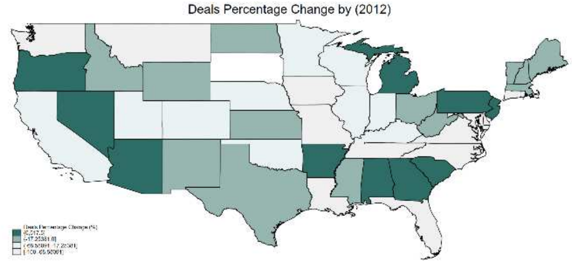
Deals Percentage Change by (2011)



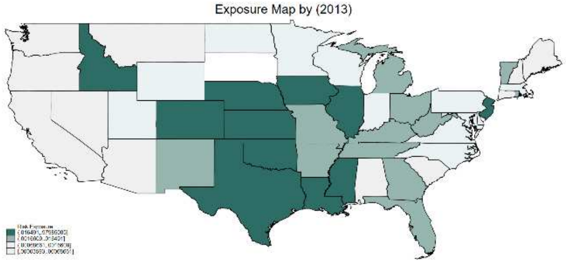
Exposure Map by (2012)



Deals Percentage Change by (2012)



Exposure Map by (2013)



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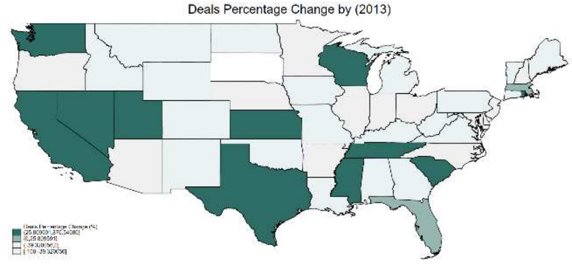

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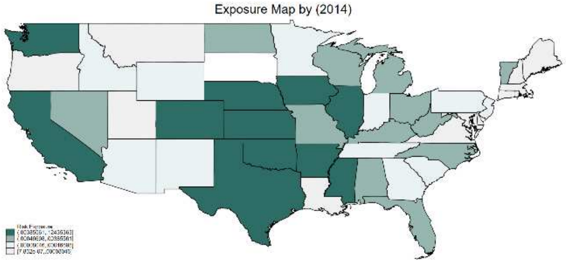
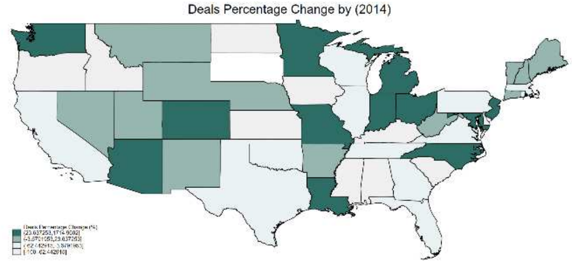
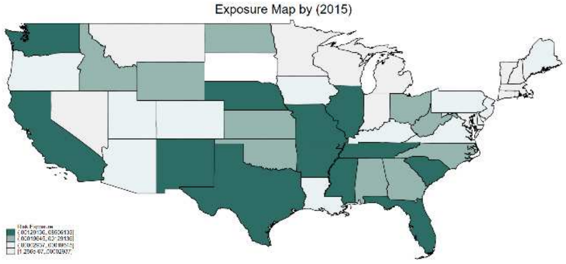


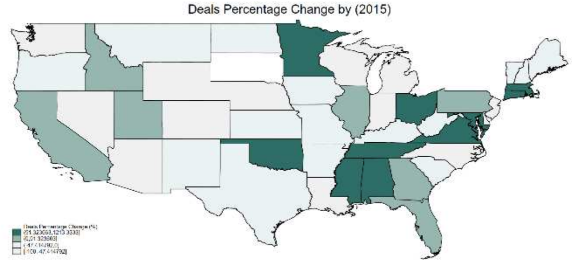
Deals Percentage Change by (2014)



Exposure Map by (2015)



Deals Percentage Change by (2015)



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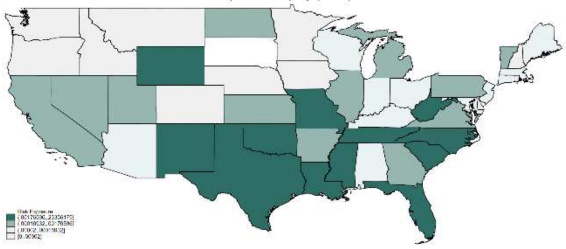
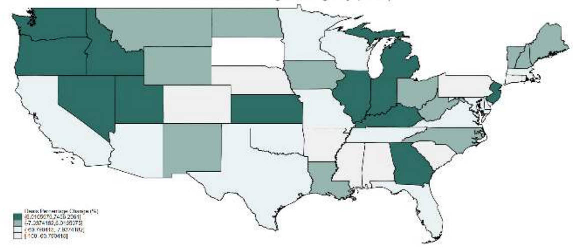
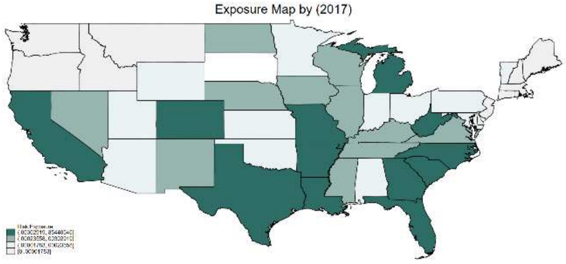


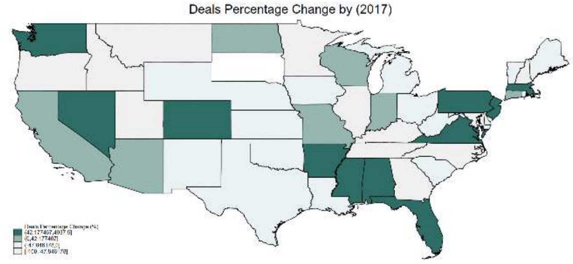
Deals Percentage Change by (2016)



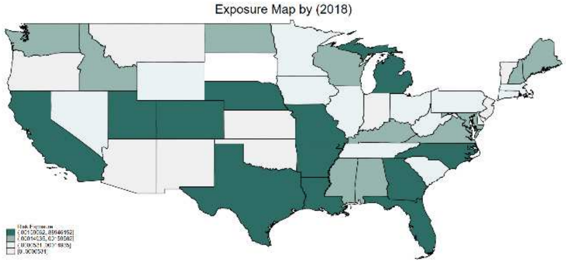
Exposure Map by (2017)



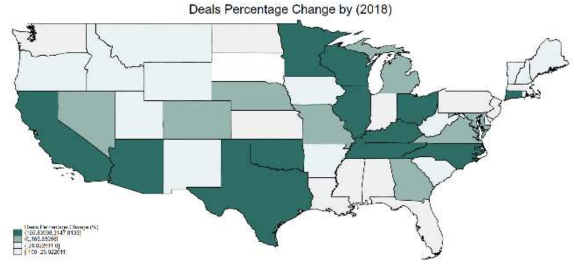
Deals Percentage Change by (2017)



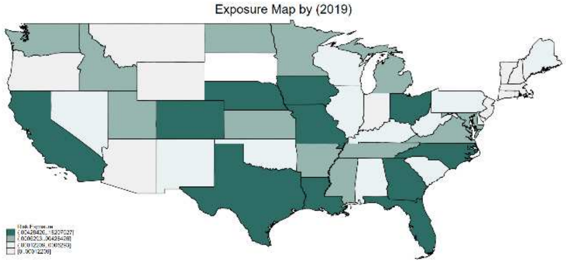
Exposure Map by (2018)



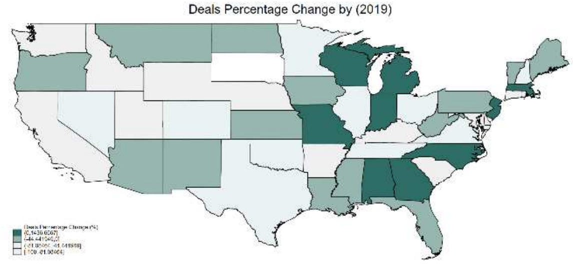
Deals Percentage Change by (2018)



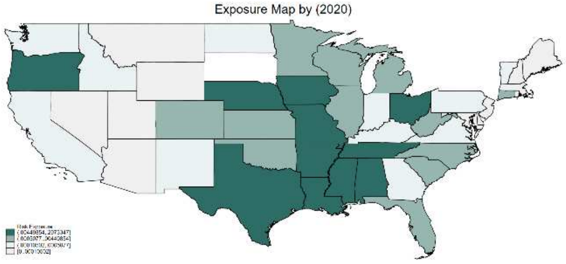
Exposure Map by (2019)



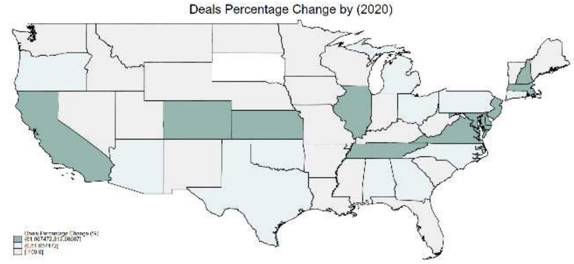
Deals Percentage Change by (2019)



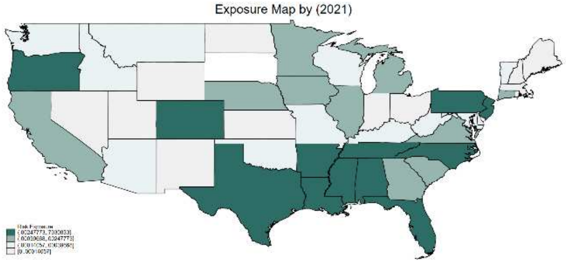
Exposure Map by (2020)



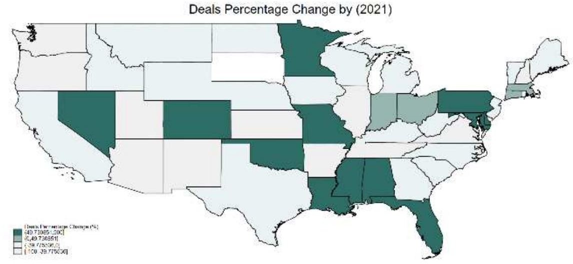
Deals Percentage Change by (2020)



Exposure Map by (2021)



Deals Percentage Change by (2021)



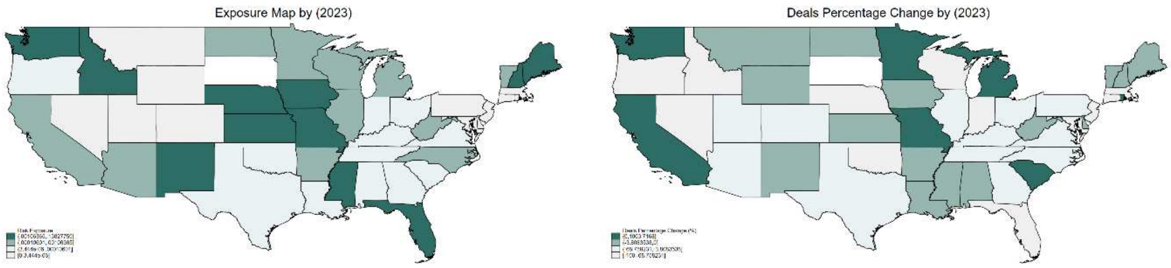



***Figure 3 Natural Hazards and Credit Supply, by Year***

This figure plots the cumulative natural hazards exposure over the cumulative 12-month rolling window and the deal percentage change (%).

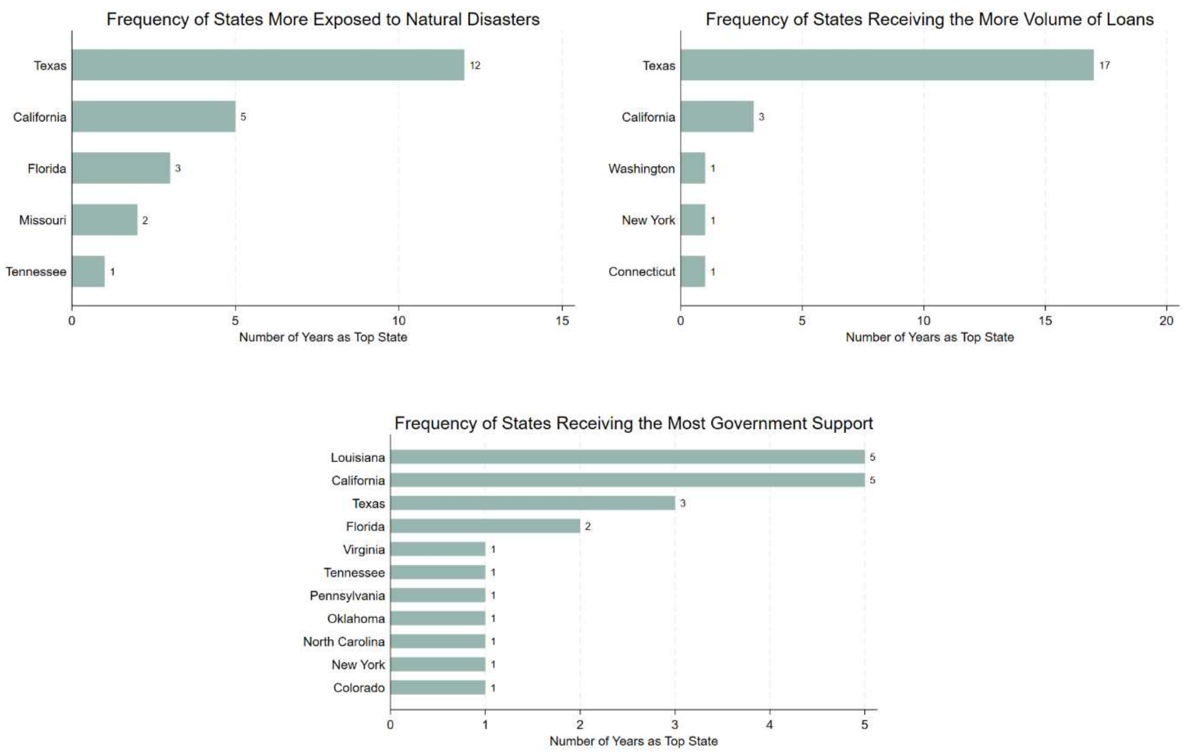



***Figure 4 Analyzing Exposure and Support for States: Frequency of Natural Disasters, Loans and Government Support***

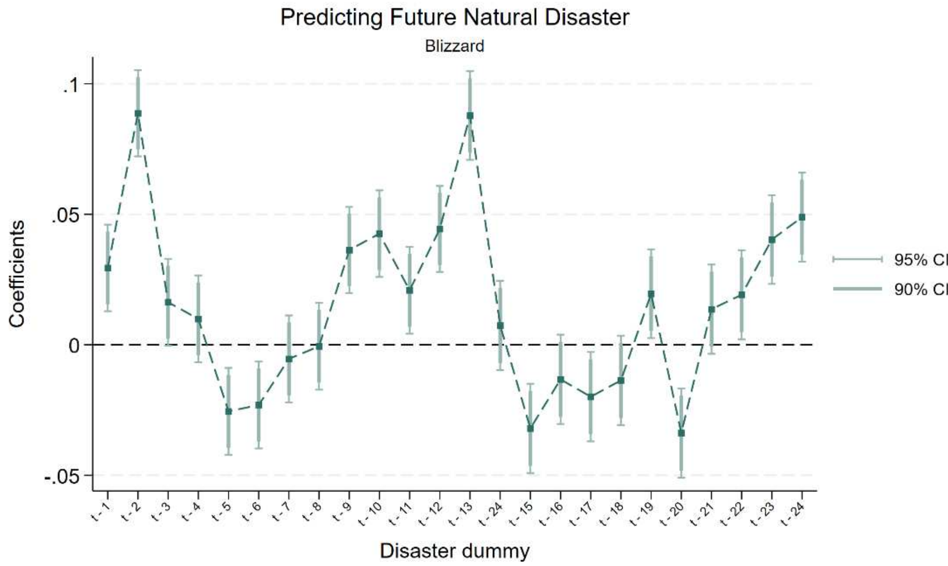



*Figure 5 Predicting Future Natural Disaster: Blizzard*

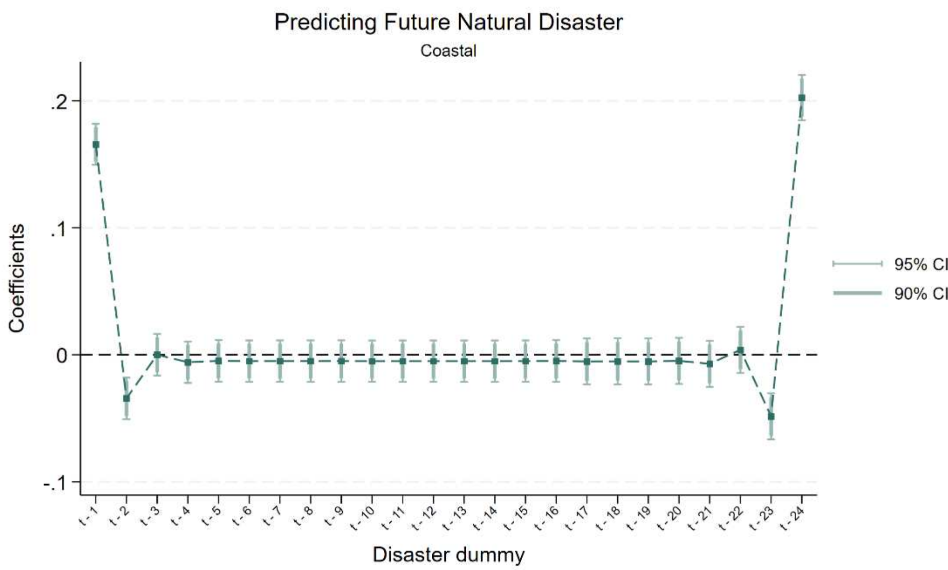



*Figure 6 Predicting Future Natural Disaster: Coastal*

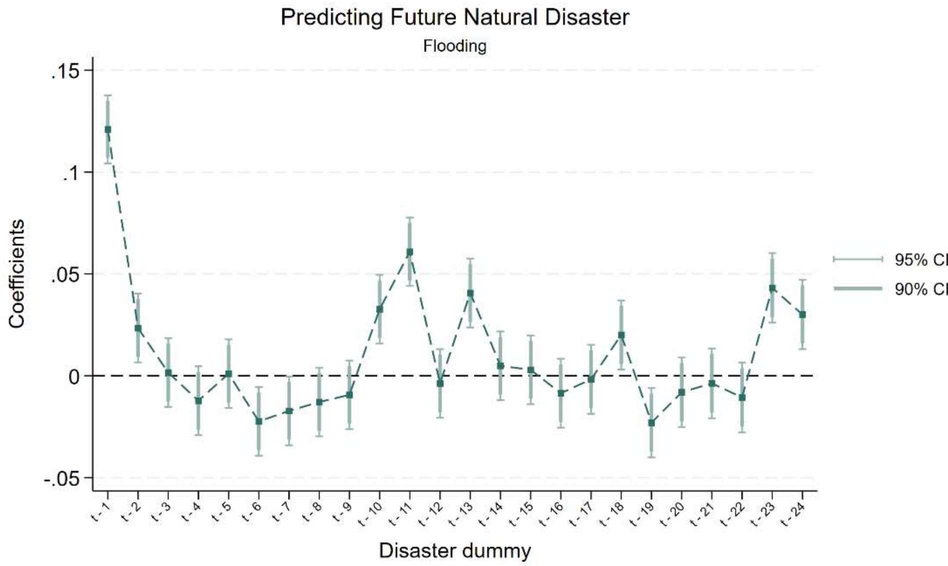



***Figure 7 Predicting Future Natural Disaster: Flooding***

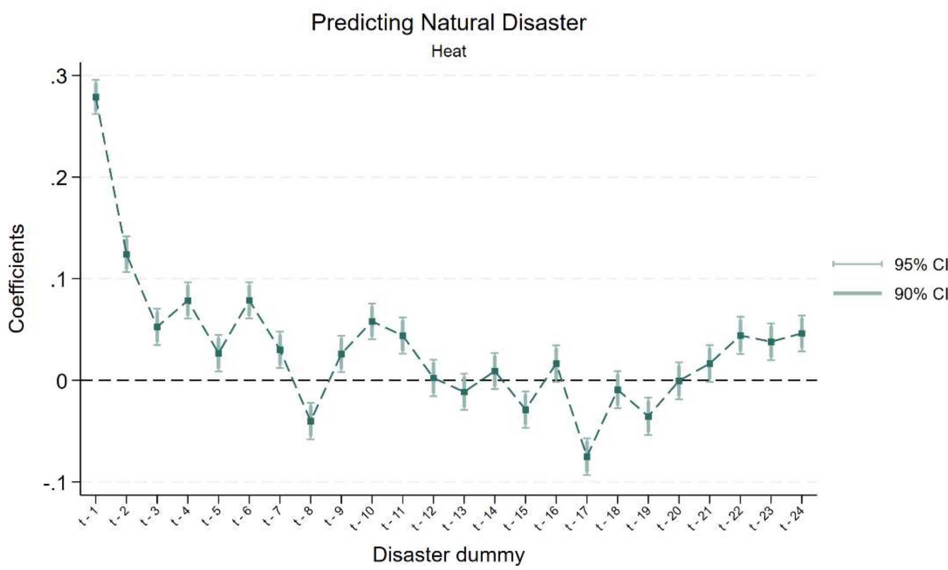



***Figure 8 Predicting Future Natural Disaster: Heat***

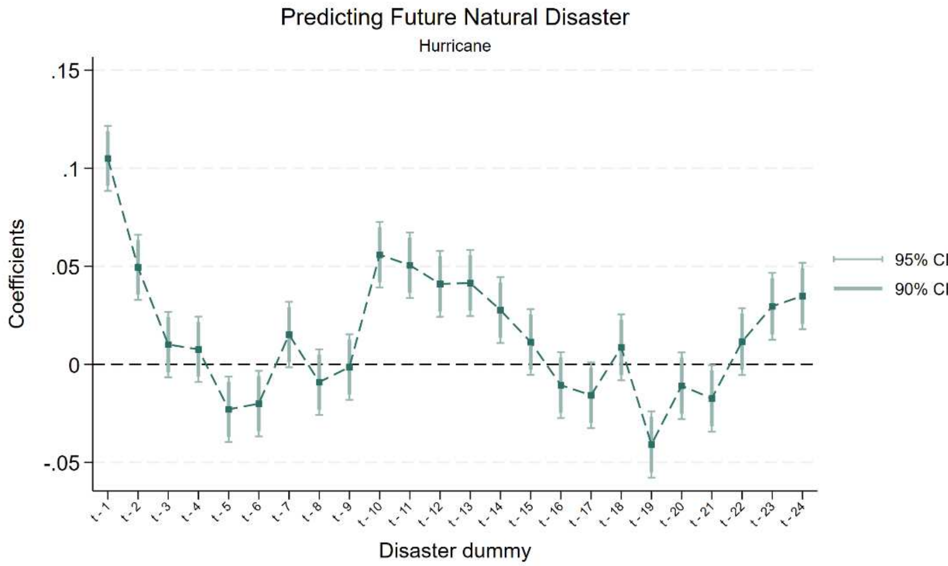



***Figure 9 Predicting Future Natural Disaster: Hurricane***

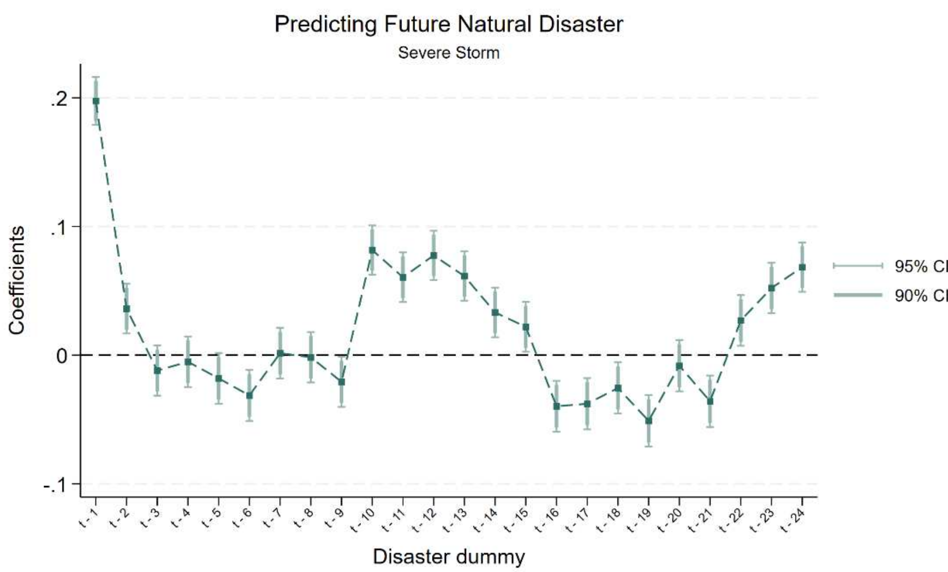



***Figure 10 Predicting Future Natural Disaster: Severe Storm***

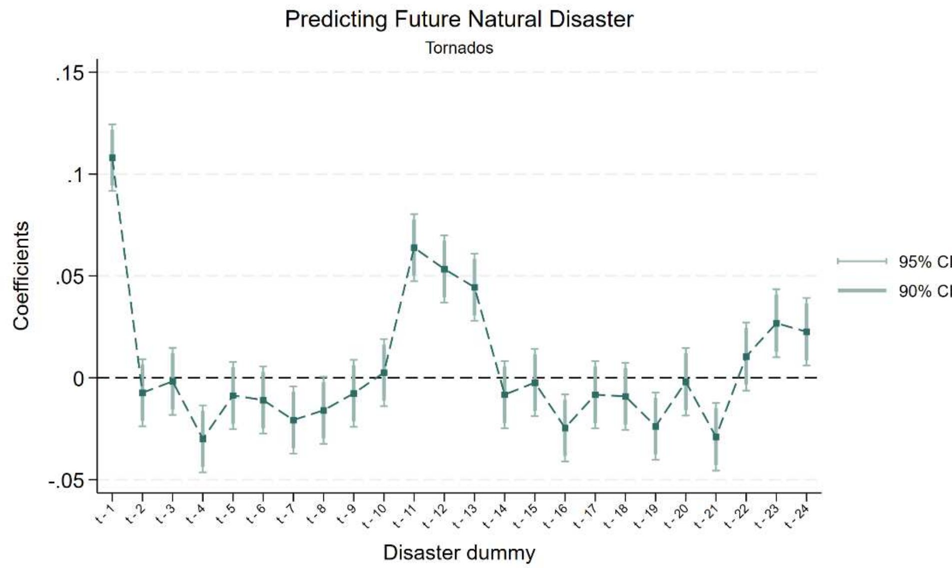



***Figure 11 Predicting Future Natural Disaster: Tornados***

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# DECLARATION

I acknowledge the use of Artificial Intelligence to improve the text quality and reduce the word count. The AI tool was employed for language refinement, including improving clarity. All content was reviewed and edited to ensure accuracy and obedience to academic standards.