Pricing and Transmission of Climate Risk in Corporate Loan

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February 2, 2026

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Preliminary and incomplete: Do not cite or circulate

Abstract

Local natural disasters are geographically concentrated shocks, yet credit markets are nationally and globally integrated, raising the question of whether physical climate risk remains local or propagates through the financial system. This paper studies how major U.S. hurricanes affect credit pricing and allocation by exploiting variation in borrowers' *ex ante* hurricane exposure using syndicated loan data and a difference-in-differences design that excludes directly damaged counties. We find that loan spreads increase significantly for more exposed borrowers following hurricanes, accompanied by declines in loan size and syndicate participation, indicating a tightening of credit conditions driven by changes in perceived risk rather than realized losses. A key contribution is to document pronounced heterogeneity across borrower types: the repricing of credit risk is concentrated among financial firms, which face large and immediate increases in borrowing costs, while non-financial firms exhibit little spread adjustment and instead adjust primarily along non-price margins. From the lender perspective, we show that banks with greater exposure to hurricane risk reallocate credit away from risky areas toward safer locations through funding- and asset-side balance-sheet channels, while nonbank lenders adjust primarily along non-price margins and partially absorb credit demand in exposed regions. Overall, the results demonstrate that localized climate disasters generate economy-wide financial spillovers through credit markets, with important implications for financial stability and the regulation of climate-related risk.

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1 Introduction

Local disasters are quintessentially geographic shocks.[1] Hurricanes, floods, and wildfires destroy physical capital, disrupt production, and depress local demand (e.g., Garmaise and Moskowitz, 2009; Cortés, 2014; Blickle et al., 2021; Billings et al., 2022; Collier et al., 2024; Gallagher and Hartley, 2025). Yet modern credit markets are nationally and globally integrated, raising a fundamental question: how do localized disaster shocks propagate through the financial system and affect aggregate credit supply and pricing? Although many studies identify spillovers (e.g., Dessaint and Matray, 2017; Cortés and Strahan, 2017; Koetter et al., 2020; Correa et al., 2025), when do the spillovers become amplification, and how are these risks shared between different lenders?

This paper studies how local disaster shocks transmit through financial intermediaries to affect credit prices, credit allocation, and aggregate risk premia. Exploiting variation in borrowers' geographic exposure to major U.S. hurricanes, we implement a difference-in-differences design that compares unaffected borrowers with high versus low disaster exposure before and after extreme weather events. We find that lenders significantly reprice credit risk following disasters. Loan spreads increase for more exposed borrowers, accompanied by declines in loan size and syndicate participation, indicating a tightening of credit conditions driven by updated risk assessments rather than contemporaneous economic disruption. Event-study evidence shows that these effects emerge immediately after disasters and dissipate over time, consistent with a repricing of near-term risk rather than permanent credit rationing.

These effects arise even in locations that experience no physical damage, indicating that disasters generate economy-wide financial spillovers through intermediary balance sheets and lending networks. Because loan prices are set by geographically diversified financial institutions, shocks that increase risk in one part of lenders' portfolios lead to adjustments in pricing and allocation across all borrowers they serve, including those located far from the disaster itself.

We provide evidence on this transmission mechanism with syndicated loans, a short-

[1] Local disasters are a direct reflection of climate change. In early 2026, extreme weather events are occurring simultaneously across regions: severe cold spells in the United States, devastating floods in Southern Africa, and large-scale wildfires in Chile that have already exceeded the damage observed during 2024, the hottest year on record. These events highlight that climate risk is immediate and recurrent.

maturity financing instrument that plays a central role in corporate investment and liquidity management. Exploiting the timing of major U.S. hurricanes—including Harvey (2017), Ian (2022), and Katrina (2005)—we implement a difference-in-differences design that compares borrowers in counties with high versus low ex ante hurricane exposure before and after disaster events, excluding directly damaged counties. This design isolates changes in perceived risk rather than realized destruction and allows us to study how lenders reprice credit even for borrowers who experience no physical damage.

Our first finding is that local disaster shocks raise loan prices well beyond the affected area. Following major hurricanes, syndicated loan spreads increase significantly for borrowers located in counties with high historical exposure to hurricanes, even when these counties are not directly hit by the event. Event-study evidence shows that these effects emerge immediately after the disaster and gradually dissipate, consistent with a repricing of near-term risk rather than permanent credit rationing. At the same time, lenders reduce loan size and syndicate participation, indicating a contraction along both the price and quantity margins.

Second, we show that this repricing operates primarily through the financial sector, with strong heterogeneity across borrower types. The increase in borrowing costs is substantially larger for financial firms, which rely heavily on short-term, relationship-based, and intermediary-provided credit. In contrast, non-financial firms are significantly less affected, especially those with greater access to bond markets and market-based financing. This pattern suggests that disaster risk is transmitted through intermediary balance sheets and lending networks, rather than through a broad deterioration in aggregate borrower fundamentals.

Third, we document that lenders differ sharply in how they transmit disaster risk, depending on their exposure and balance sheet capacity. Banks with greater geographic exposure to hurricane-prone regions raise loan spreads more aggressively and adjust loan maturity and syndicate structure more. These lenders also reallocate credit toward lower-risk borrowers, shorten maturities, and are more likely to renegotiate or amend existing contracts following disasters. These findings highlight that credit risk is not only priced, but actively reallocated across borrowers and intermediaries in response to local shocks.

Our analysis separates two conceptually distinct channels through which disasters affect credit markets. First, disasters directly affect local economic fundamentals, such as

expected cash flows and near-term default risk, which may raise borrowing costs for firms in affected or vulnerable locations. Second, and central to our contribution, disasters also generate a financial-sector shock: risk is aggregated on intermediary balance sheets, tightening funding constraints and altering lenders' pricing and risk allocation decisions economy-wide. Disentangling these channels is crucial for understanding whether disaster risk primarily reallocates credit locally or instead reshapes aggregate financial conditions.

Related Literature. This paper sits at the intersection of several literatures. First, a growing literature documents that physical climate disaster risk is priced in asset price[2] and bank lending (e.g., Koetter et al., 2020; Javadi and Masum, 2021). Correa et al. (2025) shows that after climate-related disasters, loan spreads increase for *at-risk but not directly hit* borrowers, which aligns closely with our identification strategy to exclude the directly declared disaster locations. We add that the transmission of that risk depends on who the marginal lenders are. In our evidence, the response is not uniform across intermediaries; banks retrench along key margins, while non-banks' relative role rises and becomes an important lender by providing relative more credit and longer maturity for the risky locations after the local disaster happens.

Second, a broader literature links bank geographic diversification and systemic vulnerability (e.g., Goetz et al., 2016; Chu et al., 2020; Conlon et al., 2024). A classic mechanism for how local shocks become nonlocal credit effects is through the internal capital markets and geographic integration. Cortés and Strahan (2017) shows that multimarket banks reallocate lending toward disaster-hit markets and away from connected unaffected markets, implying spatial spillovers through bank organizations. We study a different but complementary propagation mechanism. Instead of focusing only on whether credit is shifted geographically within bank organizations, we show that the terms of credit adjust even for unaffected areas with different ex ante vulnerability, and that the response differs across lenders. We bring this spillover perspective to syndicate loan outcomes and show that lenders' geographically distributed exposures translate into differential repricing and contracting behavior across

[2]Existing work has documented pricing effects for long-duration assets, particularly in housing, mortgage, and municipal bond markets (e.g., Bernstein et al., 2019; Ouazad and Kahn, 2019; Murfin and Spiegel, 2020; Goldsmith-Pinkham et al., 2023). Other studies focus on transition risk associated with the shift toward a low-carbon economy. Climate risk is capitalized into property values and borrowing costs. Much of this research emphasizes long-term assets, reflecting the belief that the economic consequences of climate change materialize gradually.

their syndicated portfolios. Moreover, the key margin is not only that banks become systemically linked, but that nonbank lenders, compared to banks, become a seemingly stabilizer in transmitting the shock through the syndicated market.

Third, a rapidly expanding literature emphasizes the rising role of nonbank lenders in debt financing (e.g., Giglio et al., 2015; Chernenko et al., 2019; Chernenko et al., 2022; Elliott et al., 2024; Aldasoro et al., 2025; Krainer et al., 2024). The literature on the substitution between bank loans and market-based finance finds that when bank credit tightens after a shock, some firms can substitute to bonds, while others remain reliant (e.g., Goel and Zemel, 2018; Schwert, 2020; Massa and Zhang, 2021; Al-Ayyoub and Phan, 2026). We find that nonbanks behave differently in pricing and transmitting physical disaster risk in syndicate loan market, compared to banks. Following hurricane shocks, banks and nonbanks adjust differently across price, quantity, and maturity. This compositional shift makes nonbanks an important marginal stabilizer and transmitter of disaster risk across borrowers and geographies.

This paper is organized as follows. Section 2 describes the data sources and construction of borrower- and lender-level exposure measures to hurricane risk. Section 3 outlines the empirical identification strategy and details the difference-in-differences design used to estimate the effects of hurricane risk on credit markets. Section 4 presents the main empirical results, documenting how hurricanes affect credit pricing and allocation from both the borrower and lender perspectives, with particular attention to heterogeneity across financial and nonbank intermediaries. Section 5 concludes.

2 Data

Our empirical analysis combines loan-level credit data with multiple sources of disaster exposure and banking geography to study how hurricane risk propagates through credit markets. We draw on detailed information on syndicated loans, which allow us to compare the responses of non-bank and bank lenders to large physical climate shocks from both the borrower and lender perspectives.

2.1 Natural Disaster Damage and Exposure

We measure local hurricane damage using data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). This data set provides comprehensive county-level information on the occurrence and economic impacts of natural disasters in the United States, including estimates of property damage associated with each event. We restrict attention to Hurricane/Tropical Storm events and construct measures of hurricane exposure at the county–month level. Focusing on hurricanes allows us to isolate a class of large, spatially concentrated shocks that generate substantial physical destruction and are plausibly exogenous to local economic conditions.

Using SHELDUS, we construct several measures of county-level hurricane exposure that capture both the frequency and severity of past events. In particular, we compute the number of hurricane events, total property damage, damage per capita, and average damage per event over the ten years preceding the sample period. These measures are intended to capture long-run local vulnerability to hurricane risk rather than realized damage from a specific event.

Table 1 summarizes the distribution of county-level hurricane exposure across U.S. counties from 2012 to 2021. Hurricane exposure is highly heterogeneous. While the median county experiences only one hurricane over a ten-year horizon and negligible associated damage, counties in the upper quartile face substantially higher event frequency and markedly larger losses, both in total and per capita terms. Across all measures, the mean substantially exceeds the median, reflecting the presence of rare but extremely destructive events. This pronounced right-skewness motivates an exposure-based empirical design that exploits cross-county variation in pre-determined hurricane vulnerability.

Table 1: Distribution of Hurricane Exposure Across U.S. Counties

	Mean	25th	50th (Median)	75th
Number of hurricanes	7.30	0	1	5
Average damage per event	105,156.50	0.43	492.64	3,437.76
Total damage per capita	138.88	0	0.15	6.74
Total property damage	12.6M	0	5,458.60	245,779.50

Notes: This table reports county-level hurricane exposure measured over the ten years preceding the sample period. Exposure measures are constructed using SHELDUS data on Hurricane/Tropical Storm events. Property damage and damage per event are expressed in 2022 dollars, while damage per capita is expressed in 2022 dollars per resident. The unit of observation is a county.

To identify major disaster events and their precise timing, we additionally use data from the Federal Emergency Management Agency (FEMA)[3] on disaster declarations. FEMA declarations allow us to distinguish hurricanes that result in federally declared disasters from other weather events and to precisely date the onset of these shocks. We use FEMA data to define event windows, exclude directly affected counties when constructing control groups, and conduct event-study analyses around major hurricanes. Combining SHELDUS-based exposure measures with FEMA declarations enables us to separate long-run vulnerability from short-run realized disaster shocks.

2.2 Syndicated Loan Data

We use syndicated loan data from DealScan, which provide comprehensive information on large corporate loan contracts in the United States. In a syndicated loan, a group of lenders jointly extends credit to a single borrower, typically coordinated by one or more lead arrangers. This institutional structure allows us to observe both the pricing and allocation of credit across multiple financial intermediaries.

[3]Under the Stafford Act, a major disaster declaration is issued by the U.S. President following a request from a state governor, and authorizes access to federal assistance programs for affected areas. Declarations are discrete indicators of severe events and do not provide a continuous measure of economic damage. In our analysis, FEMA declarations are used solely to identify the timing and geographic scope of major hurricanes, rather than to measure their economic intensity.

The unit of observation in DealScan is a loan tranche, which corresponds to a specific credit facility within a syndicated loan agreement.[4] For each tranche, we observe the loan spread over the benchmark rate, the tranche amount, maturity, reference rate, loan type, and the composition of the lending syndicate, including the identities of participating lenders and their respective shares.

We assign each tranche to the borrower's county of location using ZIP code–county crosswalks, which allows us to merge loan-level outcomes with county-level measures of hurricane exposure. We restrict the sample to U.S. borrowers and to loan facilities with complete information on pricing and contract characteristics. Because syndicated loans primarily serve medium-sized and large firms, this dataset is particularly informative for studying how physical climate risk affects the supply of corporate credit.[5]

2.3 Bank Geographic Exposure and Deposits

To measure lenders' exposure to hurricane risk, we construct bank-level exposure measures using branch and deposit data from the FDIC BankFind database. These data report the geographic distribution of bank branches and deposits at the county level. We combine this information with county-level hurricane damage from SHELDUS to compute each bank's exposure to hurricane risk as a deposit-weighted average of property damage across the counties in which the bank operates. This approach captures the extent to which a bank's funding base is exposed to local disaster risk and allows us to analyze credit supply responses from the lender perspective, even when banks themselves are not headquartered in affected areas.

[4] A syndicated loan agreement may include multiple tranches that differ in maturity, pricing, and contractual features but are issued simultaneously to the same borrower.

[5] To examine credit outcomes for small firms, we complement the syndicated loan analysis with data from the U.S. Small Business Administration (SBA). In particular, we use SBA 7(a) loan data, which cover government-guaranteed loans originated by banks and non-bank lenders to small businesses that typically lack access to syndicated credit markets. The 7(a) program is the SBA's largest lending program and provides detailed information on loan terms, interest rates, loan amounts, maturity, lender identity, and borrower location, making it well suited for analyzing disaster-related credit responses among small firms.

2.4 Measuring Hurricane Exposure

We construct a county-level measure of *ex ante* hurricane risk using the Spatial Hazard Events and Losses Database for the United States. The data are reported at the county–month level and include the number of recorded events and inflation-adjusted damages (in 2022 dollars). Throughout, we restrict attention to the hurricane and tropical storm hazard category. This county-level object is the common building block for all exposure measures below; the only difference across the borrower and lender perspectives is how county risk is mapped into borrower- or lender-specific exposure indices.

2.4.1 Borrower perspective

From the borrower's perspective, hurricane exposure is determined by the historical vulnerability of the county in which the borrower is located. The objective is to capture *ex ante* physical climate risk—reflecting long-run exposure to hurricanes—rather than contemporaneous damage from the focal event. We therefore construct county-level exposure measures based on historical hurricane activity and damages, and assign these measures to borrowers according to their geographic location.

For each county k and month t, SHELDUS reports event counts $\text{Events}_{k,t}$ and damages, including property damage $\text{PropDmg}_{k,t}$ and crop damage $\text{CropDmg}_{k,t}$. We define total damages as

$$\text{TotDmg}_{k,t} = \text{PropDmg}_{k,t} + \text{CropDmg}_{k,t},$$

and also consider per-capita analogues.

Our exposure measure captures a county's *ex ante vulnerability* to hurricanes based on its historical experience, rather than realized damage from the focal event. We construct a balanced county–month panel and compute rolling exposure measures over the prior ten years (120 months), excluding the current month. Our baseline monthly exposure measure is the rolling mean of property damages,

$$\text{Exposure}_{k,t}^{\text{Loc}} \equiv \frac{1}{120} \sum_{s=t-120}^{t-1} \text{PropDmg}_{k,s}$$

We analogously construct alternative exposure measures using total damages, per-capita

damages, cumulative sums of events and damages, and intensity measures defined as average damage per event over the same rolling window (damage divided by event counts, set to zero when no events occur). Together, these measures capture frequency, magnitude, and intensity of hurricane risk.

For a hurricane event occurring in month t_0, we summarize pre-event vulnerability by collapsing the monthly exposure into a single county-level index,

$$\text{Exposure}_k^{\text{Loc}} \equiv \frac{1}{12} \sum_{m=t_0-12}^{t_0-1} \text{Exposure}_{k,m}^{\text{Loc}}$$

We compute $\text{Exposure}_k^{\text{Loc}}$ only for counties that are not directly affected according to FEMA disaster declarations. Unaffected counties are then classified into exposure quartiles based on $\text{Exposure}_k^{\text{Loc}}$, with the top quartile forming the high-exposure group and the bottom quartile forming the low-exposure group.

Finally, we assign exposure to borrowers by mapping each loan to the borrower's county using ZIP code–county crosswalks. Let $\text{k}(j)$ denote borrower j's county. The borrower's hurricane exposure is:

$$E_j \equiv \text{Exposure}_{\text{k}(j)}^{\text{Loc}} \tag{1}$$

2.4.2 Lender perspective

From the lender's perspective, exposure to hurricane risk reflects the extent to which a financial institution is connected—directly or indirectly—to disaster-prone locations through its balance sheet. Even when lending to borrowers in unaffected areas, lenders may adjust credit supply if a large disaster alters funding conditions or the risk profile of their existing loan portfolios. To capture these channels, we construct lender-level exposure measures that aggregate county-level hurricane risk according to lenders' geographic deposit footprints and the spatial distribution of their outstanding syndicated loans.

We construct lender-level exposure to hurricane risk by combining the same county-level vulnerability measure $\text{Exposure}_k^{\text{Loc}}$ with lender-specific geographic weights. In our implementation, the county risk input used in the lender measures is

$$\text{DisasterRisk}_k \equiv \text{Exposure}_k^{\text{Loc}} \tag{2}$$

Deposit-Based Lender Exposure (Funding Channel): Using branch-level deposit data aggregated to the lender–county level, we compute the share of lender i's total deposits located in county k,

$$\text{DepShare}_{ik} = \frac{\sum_{b \in k} \text{Deposit}_{ib}}{\sum_{b} \text{Deposit}_{ib}},$$

where b indexes branches of lender i. We then define lender exposure through deposits as:

$$\text{Exposure}_i^{\text{Deposit}} = \sum_{k \in \mathcal{K}} \text{DepShare}_{ik} \times \text{DisasterRisk}_k \tag{3}$$

Syndicated-Loan–Based Lender Exposure (Asset Channel): Using Dealscan, we construct the distribution of lender i's outstanding syndicated loan portfolio across borrower counties at the event date. Let LoanShare_{ik} denote the share of lender i's total outstanding syndicated loan exposure extended to borrowers in county k,

$$\text{LoanShare}_{ik} = \frac{\text{TotalLoan}_{ik}}{\text{TotalLoan}_{i}}.$$

We then define asset-side exposure as:

$$\text{Exposure}_i^{\text{Loan}} = \sum_{k \in \mathcal{K}} \text{LoanShare}_{ik} \times \text{DisasterRisk}_k \tag{4}$$

Together, these two measures allow us to separately identify funding-side and asset-side channels through which localized hurricane shocks propagate through financial intermediaries. While deposit-based exposure reflects vulnerability through funding networks, loan-based exposure captures transmission through credit portfolios and borrower linkages.

3 Empirical Strategy

In this section, we describe our empirical strategy to estimate how financial intermediaries adjust credit terms in response to large and salient physical climate shocks. The unit of observation is a loan tranche ℓ extended by lender b to a borrower located in county k at time t, measured at a monthly frequency. We focus on three primary loan outcomes: the loan spread over the benchmark rate (measured in basis points), the number of lenders

participating in the syndicate, and the logarithm of the tranche amount. These outcomes jointly capture the price and quantity dimensions of credit supply.

Our empirical framework is general and applies to multiple channels through which climate risk may affect credit markets. Across specifications, the identifying variation comes from differences in exposure to physical climate risk, while the underlying econometric design remains the same. The key distinction across analyses lies in how exposure is defined—whether based on the borrower's location, the lender's funding footprint, or the lender's existing credit portfolio.

A central objective of the analysis is to study heterogeneity in lenders' responses. In particular, we examine whether bank lenders and non-bank lenders adjust credit pricing and allocation differently following large climate shocks, reflecting differences in balance-sheet constraints, funding structures, and risk-bearing capacity. In addition, we explore heterogeneity on the borrower side by contrasting financial and non-financial firms, which differ in their exposure to aggregate funding conditions and in their role within the credit intermediation network. We implement this framework using case studies of major U.S. hurricanes that caused substantial economic disruption and received extensive national attention, including Hurricane Ian (2022), Hurricane Harvey (2017), and Hurricane Katrina (2005). These events generate sharp and well-defined shocks to perceived physical climate risk and are plausibly exogenous to contemporaneous credit conditions, making them well suited for quasi-experimental analysis.

3.1 Treatment and Control Groups

We define treatment and control groups based on cross-county variation in *ex ante* hurricane exposure from the borrower's perspective, following a growing literature that studies how credit markets respond to changes in perceived disaster risk rather than realized local damage. To isolate belief-updating effects from the direct economic disruption caused by hurricanes, we exclude counties that are directly declared disaster areas for the focal event from the estimation sample.

Identification relies on comparing borrowers located in counties that are not directly affected by the hurricane but differ in their historical exposure to hurricane risk. This comparison allows us to study how lenders adjust credit supply in response to updated

assessments of future disaster risk, rather than contemporaneous shocks to borrower cash flows, asset values, or local economic activity. Our approach closely follows Correa et al. (2025), who similarly focus on indirectly exposed locations to disentangle risk perception effects from realized damage.

To ensure comparability between treated and control observations, we further restrict the sample to counties that have experienced hurricane exposure in the past. Counties with no historical hurricane exposure are excluded, as they differ systematically from hurricane-prone counties along geographic, economic, and institutional dimensions—such as distance from the coast, industrial composition, insurance coverage, and baseline disaster preparedness—and therefore do not constitute an appropriate counterfactual.

Within the set of historically hurricane-exposed counties, we rank locations by their historical exposure measure E_k, defined in Section 2.4, and partition the distribution into quartiles. Counties in the highest quartile are classified as *high-exposure* counties, while counties in the lowest quartile form the control group. By focusing on variation within the hurricane-risk universe, the empirical design isolates the effect of being *more exposed rather than less exposed* to hurricanes, holding fixed broader geographic and institutional characteristics associated with hurricane-prone regions.

An analogous treatment classification is used in the lender-based analysis, except that exposure is defined at the lender level based on balance-sheet connections to hurricane-prone counties, rather than at the borrower's county of location.

3.2 Event Timing and Treatment Definition

Let T_k denote the month in which the focal hurricane occurs for county k. We define a post-event indicator

$$\text{Post}_{kt} = \mathbb{1}\{t > T_k\}, \tag{5}$$

which equals one for loans originated after the hurricane and zero otherwise.

The treatment variable is defined as the interaction

$$\text{HighExposure}_k \times \text{Post}_{kt},$$

which captures differential changes in credit conditions for borrowers located in counties with

high historical hurricane exposure following the event. This interaction tests whether lenders adjust loan terms more strongly in locations that were already perceived as vulnerable to hurricanes prior to the shock.

Throughout the analysis, counties directly declared as disaster areas for the focal hurricane are excluded. As a result, identification relies exclusively on borrowers located in *non-affected counties* that differ only in their ex ante hurricane vulnerability.

3.3 Baseline Difference-in-Differences Specification

Our empirical strategy relies on a difference-in-differences design that compares loan terms before and after major hurricane events across units that differ in their *ex ante* exposure to hurricane risk. The econometric specification is common across borrower- and lender-based analyses, with the key distinction being the level at which treatment is defined.

In the borrower-based analysis, treatment status is defined at the location (county) level based on historical hurricane exposure at the borrower's location. In the lender-based analysis, treatment status is instead defined at the lender level based on balance-sheet exposure to hurricane-prone locations through deposits or existing loan portfolios. Accordingly, identification in the borrower analysis exploits within-lender, cross-location variation over time, while identification in the lender analysis exploits within-location, cross-lender variation over time.

We estimate the following baseline difference-in-differences regression:

$$y_{\ell bkt} = \beta \left(\text{HighExposure}_u \times \text{Post}_{kt}\right) + X'_{\ell bkt}\gamma + \alpha_k + \alpha_b + \alpha_t + \alpha_{\text{industry}} + \varepsilon_{\ell bkt}, \qquad (6)$$

where $y_{\ell bkt}$ denotes a loan-level outcome—such as the loan spread over the benchmark rate, the number of lenders in the syndicate, or the logarithm of the tranche amount—observed for loan tranche ℓ extended by lender b to a borrower located in county k at time t. The vector $X_{\ell bkt}$ includes loan characteristics, most notably maturity.

The treatment indicator HighExposure_u equals one for units in the top quartile of historical hurricane exposure and zero for units in the bottom quartile. The index u denotes the relevant unit of exposure: $u = k$ in the borrower-based analysis and $u = b$ in the lender-based analysis. The indicator Post_t equals one for loan originations occurring after the hurricane event and zero otherwise.

Location fixed effects α_k absorb time-invariant local characteristics, including geography, baseline economic conditions, and long-run disaster risk. Lender fixed effects α_b control for persistent differences in pricing policies, balance-sheet structure, and risk tolerance across financial institutions. Loan-month fixed effects α_t absorb aggregate credit market conditions, including monetary policy and financial cycle dynamics. Borrower industry fixed effects α_{industry} account for systematic differences in credit demand and risk across sectors.

In the borrower-based specification, identification relies on within-lender, cross-location variation over time among counties that are not directly affected by the hurricane but differ in their historical vulnerability. The coefficient β captures the average differential change in loan terms for borrowers located in high-exposure locations relative to low-exposure locations following the hurricane.

In the lender-based specification, identification instead relies on within-location, cross-lender variation over time, comparing how more-exposed and less-exposed lenders adjust credit terms to borrowers in the same county following the disaster. In this case, β captures the effect of lender balance-sheet exposure to hurricane risk on credit supply.

All regressions cluster standard errors at the lender level. This accounts for arbitrary correlation in unobserved shocks across loans originated by the same bank, which may arise due to centralized pricing policies, balance-sheet constraints, or portfolio-wide risk management practices. Because lenders are the primary decision-making unit in syndicated loan pricing, clustering at the lender level is the appropriate level for statistical inference.

The key identifying assumption underlying equation (6) is a parallel trends condition: absent the hurricane, loan outcomes for high- and low-exposure units would have evolved similarly over time. Formally,

$$\mathbb{E}[y_{u,t+k'} - y_{u,t-1} \mid \text{HighExposure}_u = 1] = \mathbb{E}[y_{u,t+k'} - y_{u,t-1} \mid \text{HighExposure}_u = 0], \qquad (7)$$

for all $k' \geq 0$. We assess the plausibility of this assumption using event-study specifications that allow for flexible pre-trends.

A second identifying assumption is that the timing of major hurricanes is exogenous to bank lending decisions at the monthly frequency relevant for loan origination. While lenders may account for long-run regional climate risk, the precise occurrence and severity of hurricanes are not predictable at short horizons and are orthogonal to contemporaneous

bank–borrower matching.

3.4 Dynamic Effects and Event-Study Specification

To study the dynamic adjustment of credit terms and to assess the validity of the parallel trends assumption, we complement the baseline difference-in-differences analysis with an event-study specification. This framework traces the evolution of loan outcomes in the months surrounding a major hurricane for units with high versus low *ex ante* exposure.

Let T_k denote the disaster month associated with the focal hurricane for county k. We define relative event time as $\tau = t - T_k$, where t denotes the loan origination month. We estimate the following regression:

$$y_{\ell bkt} = \sum_{\tau \neq -1} \beta_\tau \left(\mathbb{1}\{t - T_k = \tau\} \times \text{HighExposure}_u \right) + X'_{\ell bkt}\gamma + \alpha_k + \alpha_b + \alpha_t + \alpha_{\text{industry}} + \varepsilon_{\ell bkt}, \quad (8)$$

where $\mathbb{1}\{t - T_k = \tau\}$ is an indicator equal to one if the loan is originated τ months relative to the hurricane. The month immediately preceding the event ($\tau = -1$) is omitted and serves as the reference period.

The indicator HighExposure_u equals one for units in the top quartile of historical hurricane exposure and zero for units in the bottom quartile. As in the baseline specification, the index u denotes the relevant unit of exposure: $u = k$ in the borrower-based analysis and $u = b$ in the lender-based analysis.

The coefficients β_τ for $\tau < 0$ capture differential pre-trends between high- and low-exposure units prior to the hurricane and provide a direct test of the identifying assumption underlying the difference-in-differences design. The coefficients for $\tau \geq 0$ trace the dynamic response of credit terms following the event and characterize the timing and persistence of lenders' adjustments to heightened perceived hurricane risk.

As in the baseline analysis, we exclude counties that are directly declared disaster areas for the focal hurricane. Consequently, the estimated dynamics reflect changes in perceived disaster risk rather than the direct effects of realized local damage. Standard errors are clustered at the lender level to account for correlation in loan outcomes driven by bank-level pricing policies and portfolio-wide adjustments.

4 Results and Discussion

This section presents the main empirical results on how major hurricanes affect credit pricing and allocation in U.S. loan markets. We focus primarily on Hurricane Harvey,[6] which provides a sharp and salient shock to perceived physical climate risk. From the borrower perspective, we study credit supply responses following Harvey and contrast these findings with evidence from Hurricane Katrina (2005) and Hurricane Ian (2022) to assess how lenders' responses to hurricane risk have evolved over time. We also incorporate SBA 7(a) loan data to capture credit responses among small firms and examine heterogeneity between financial and non-financial borrowers.

We then shift to the lender perspective to study how hurricane risk propagates through financial intermediaries' balance sheets via funding and asset channels, highlighting mechanisms of risk transmission and risk sharing. A key additional finding is that nonbank lenders play a stabilizing role in exposed regions: relative to banks, nonbanks adjust less through spreads and instead expand credit along non-price margins—extending larger loan amounts and longer maturities in risky locations—while exhibiting little systematic response in safe locations. Together, the results show that hurricane shocks reshape both the pricing of climate risk and the allocation of credit across borrower types and lender business models.

4.1 Harvey Hurricane: Borrower's Perspective

We study the effects of major hurricanes from the borrower's perspective. We first present results for all borrowers following Hurricane Harvey and compare these findings with evidence from Hurricane Ian and Hurricane Katrina, as well as with results from SBA loan data to capture credit responses among small firms. We then examine heterogeneity in credit responses between financial and non-financial borrowers, highlighting differences in how climate risk is priced across borrower types.

[6] Hurricane Harvey made landfall in Texas in August 2017, causing severe flooding and becoming one of the costliest hurricanes in U.S. history. Beyond the directly affected counties, the event heightened perceptions of hurricane-related risk across the Gulf Coast, making it a salient case for studying how lenders adjust credit supply in response to perceived physical climate risk.

All borrowers. We begin by examining the average effect of Hurricane Harvey on syndicated loan terms across all borrowers, pooling financial and non-financial firms.

Table 2 reports difference-in-differences estimates of the impact of Hurricane Harvey on syndicated loan contract terms, using borrowers' historical hurricane exposure to define treatment intensity. The dependent variables are the loan spread over the benchmark rate, the number of lenders in the syndicate, and the logarithm of the tranche amount.

Columns (1)–(3) compare borrowers located in counties in the highest quartile of historical hurricane exposure to those in the lowest quartile, excluding counties directly declared as disaster areas. Following Hurricane Harvey, this extreme exposure contrast yields large and statistically significant effects: loan spreads increase sharply, syndicate size declines, and tranche amounts fall. These results indicate a pronounced tightening of credit conditions for borrowers located in counties with substantially higher *ex ante* hurricane vulnerability, even in the absence of realized local damage.

Columns (4)–(6) broaden the treatment group to include counties in the upper half of the exposure distribution. Relative to the Q4–Q1 comparison, the estimated effects are smaller and less precisely estimated, consistent with a reduced difference in underlying hurricane exposure between treated and control groups when moderately exposed counties are included. This attenuation suggests that lenders' credit supply responses scale with the intensity of historical exposure, with the strongest adjustments occurring when the contrast in perceived hurricane risk is largest. Taken together, the results indicate that lenders reprice and reallocate credit most strongly in response to large differences in *ex ante* climate risk, adjusting both price and quantity margins as perceived hurricane vulnerability increases.

Table 2: Hurricane Harvey Impact on Syndicated Loan Terms

	(1) Margin BPS	(2) No. Lenders	(3) Ln Amount	(4) Margin BPS	(5) No. Lenders	(6) Ln Amount
DID	69.235***	-1.808***	-0.316**	27.067	-1.746***	-0.184
	(16.28)	(0.54)	(0.13)	(16.58)	(0.46)	(0.12)
Tenor Maturity	1.017***	0.038***	0.008***	1.053***	0.038***	0.010***
	(0.13)	(0.00)	(0.00)	(0.13)	(0.00)	(0.00)
Observations	6,343	6,343	6,343	8,713	8,713	8,713
R^2	0.619	0.657	0.608	0.631	0.691	0.616

Notes: This table reports the Difference-in-Differences results for Hurricane Ian using borrower's exposure. Columns (1)-(3) compare high-exposure counties (Q4) to the control group. Columns (4)-(6) expand the treatment to all exposed counties (Q2-Q4). Standard errors are clustered at the lender level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

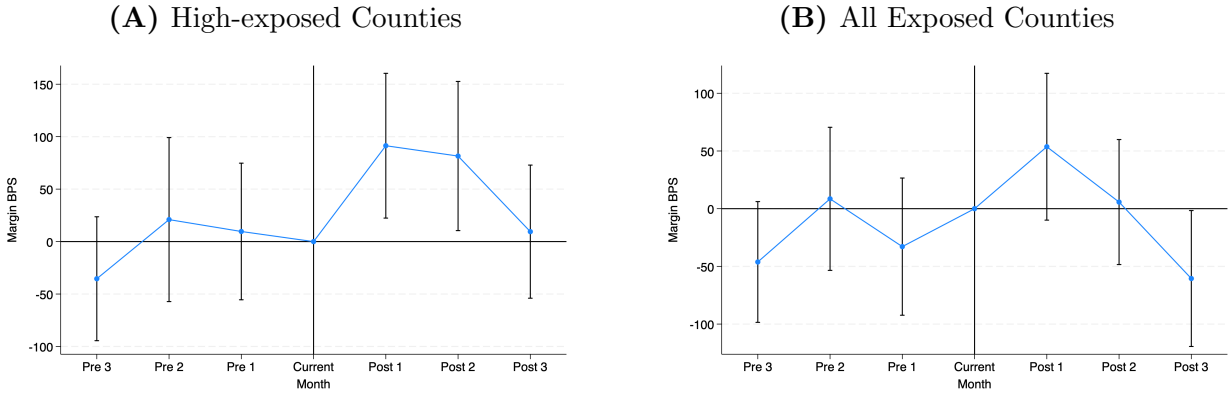
Figure 1 presents event-study estimates of the effect of Hurricane Harvey on syndicated loan spreads from the borrower's perspective. The figure reports coefficients from a dynamic difference-in-differences specification, with event time defined relative to the hurricane month ($t = 0$) and the month immediately prior to the event omitted as the reference period. Panel (A) focuses on borrowers in counties in the highest quartile of historical hurricane exposure, while Panel (B) expands the treatment group to include all exposed counties.

In both panels, pre-event coefficients are small and statistically indistinguishable from zero, supporting the parallel trends assumption. Following the hurricane, Panel (A) shows a clear and persistent increase in loan spreads for borrowers in highly exposed counties, indicating a tightening of credit conditions driven by heightened perceptions of climate risk. This dynamic pattern closely mirrors the static difference-in-differences results. By contrast, when the treatment group is broadened to include all exposed counties in Panel (B), the post-event coefficients are smaller and not statistically significant. This attenuation reflects the inclusion of moderately exposed counties, which reduces the contrast in hurricane vulnerability relative to the control group. Overall, the evidence indicates that lenders' repricing of credit risk following Hurricane Harvey is concentrated in locations with the greatest historical exposure to hurricanes.

Consistent with these findings for syndicated loans, we observe similar dynamics in small business credit markets. Figure 7 reports event-study estimates for interest rates on SBA 7(a)

loans around Hurricane Harvey. As in the syndicated loan analysis, pre-event coefficients are small and statistically indistinguishable from zero, supporting parallel trends. Following the hurricane, interest rates on SBA 7(a) loans increase in the post-event period, with the largest response occurring one month after the event. Although the estimates are less precisely measured, likely reflecting greater heterogeneity among small borrowers, the direction and timing of the response closely mirror the repricing observed in syndicated loan markets. Taken together, these results indicate that hurricane-induced increases in perceived climate risk transmit to both large corporate borrowers and small businesses.

Figure 1: Harvey Impact on Syndicate Loan Spread



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The sample includes all borrowers. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event.

We also estimate dynamic event-study specifications for additional credit supply margins, namely the syndicated loan tranche amount and the number of participating lenders. The corresponding figures are reported in Appendix Figures 8 and 9. While these specifications follow the same empirical design as the loan spread analysis, the estimated pre-trends are not flat, particularly for quantity-based outcomes. As a result, the parallel trends assumption underlying the difference-in-differences framework is less credible for these outcomes, and we refrain from drawing causal conclusions from the dynamic patterns. We therefore focus our interpretation on the loan spread results, for which pre-trends are more stable and the

identifying assumptions are more plausible.

To place the Harvey results in a broader temporal context, we compare them to two other major hurricanes that occurred at very different points in time: Hurricane Katrina (2005) and Hurricane Ian (2022). These events allow us to assess whether lenders' credit supply responses to hurricane risk have evolved as awareness, salience, and pricing of climate risk have changed.

We first examine Hurricane Katrina[7] , which struck the U.S. Gulf Coast in August 2005, well before climate risk featured prominently in financial regulation, risk management, or market discourse. Appendix Table 9 reports difference-in-differences estimates using the same borrower-exposure design. In contrast to Harvey, we find no evidence of an increase in loan spreads for borrowers located in more exposed counties following Katrina. Instead, adjustment occurs primarily along quantity margins, with declines in syndicate size and tranche amounts. Appendix Figure 13 confirms the absence of a systematic post-event increase in spreads. Taken together, these results suggest that in the mid-2000s lenders responded to hurricane risk mainly by contracting credit quantities, rather than repricing risk.

We then turn to Hurricane Ian [8], which made landfall in Florida in September 2022, at a time when physical climate risk was already widely recognized by financial institutions, regulators, and investors. Appendix Table 8 and Appendix Figure 10 show that, as in the Harvey case, loan spreads increase significantly for borrowers in more exposed counties, particularly when comparing the highest-exposure quartile to the lowest. As before, the estimated effects attenuate when moderately exposed counties are included, indicating that lenders' repricing responses scale with the intensity of *ex ante* hurricane risk.

Viewed together, the comparison across Katrina, Harvey, and Ian reveals a clear evolution

[7]Hurricane Katrina struck the U.S. Gulf Coast in August 2005 and generated unprecedented humanitarian and economic losses, particularly in Louisiana and Mississippi. Importantly, Katrina occurred well before physical climate risk became a standard consideration in credit markets, risk management practices, or regulatory stress testing, making it a useful early-period benchmark for lenders' responses to large natural disasters prior to the widespread pricing of climate risk.

[8]Hurricane Ian made landfall in Florida in September 2022 and ranks among the most destructive hurricanes in recent U.S. history, generating large insured losses, widespread infrastructure damage, and substantial media and regulatory attention. As with Hurricane Harvey, although realized damage was concentrated in officially declared disaster areas, the event plausibly shifted lenders' perceptions of hurricane risk across a broader set of exposed counties, making Ian a useful case for assessing the external validity of the credit market responses documented above.

in credit market responses to physical climate risk. While earlier disasters primarily triggered quantity adjustments, more recent hurricanes lead to sharp and systematic repricing of credit risk. This pattern is consistent with an increasing integration of physical climate risk into lenders' pricing decisions over time.

Financial borrowers. We now focus on financial firms, which are tightly connected to funding markets and may therefore be particularly sensitive to shocks that affect lenders' balance sheets and risk perceptions.

Table 3 examines whether the borrower-level effects of Hurricane Harvey are concentrated among financial firms. We restrict the sample to financial borrowers, defined as firms with four-digit SIC codes between 6000–6499 and 6700–6799. The results show a large and highly statistically significant increase in loan spreads for financial borrowers located in high-exposure counties following the hurricane. The estimated increase in margins—on the order of 115–120 basis points—is substantially larger than in the full-sample analysis, indicating a pronounced tightening of credit pricing for financial firms.

Consistent with a contraction in credit supply along non-price dimensions, we also observe sizable declines in both the number of lenders participating in syndicates and in tranche amounts. These effects are robust when the treatment group is expanded to include all exposed counties (Q2–Q4), suggesting that lenders respond particularly strongly to hurricane risk when extending credit to financial firms, which are more tightly linked to aggregate funding conditions and balance-sheet risk.

Table 3: Harvey Impact on Syndicated Loan Terms: Financial Borrowers

	(1) Margin BPS	(2) No. Lenders	(3) Ln Amount	(4) Margin BPS	(5) No. Lenders	(6) Ln Amount
DID	119.812***	-4.419***	-0.480**	115.221***	-4.558***	-0.546***
	(22.89)	(0.72)	(0.20)	(21.27)	(0.63)	(0.20)
Tenor Maturity	1.056***	0.025***	-0.001	1.091***	0.041***	0.003
	(0.22)	(0.01)	(0.00)	(0.22)	(0.01)	(0.00)
Observations	1861	1861	1861	2415	2415	2415
R^2	0.638	0.835	0.596	0.686	0.857	0.538

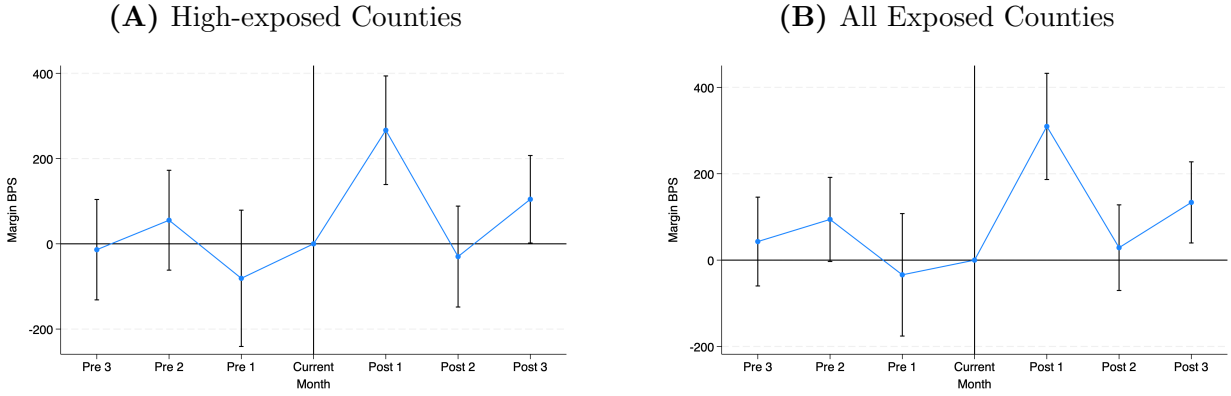
Notes: This table reports Difference-in-Differences estimates of the impact of Hurricane Harvey using borrower exposure. The sample is restricted to financial borrowers, defined as firms with four-digit SIC codes 6000–6499 and 6700–6799. Columns (1)-(3) compare high-exposure counties (Q4) to the control group. Columns (4)-(6) expand the treatment to all exposed counties (Q2-Q4). Standard errors are clustered at the lender level and reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2 presents event-study estimates of the impact of Hurricane Harvey on syndicated loan spreads for financial borrowers. Consistent with the static results in Table 3, loan spreads increase sharply following the hurricane for borrowers located in more exposed counties. The post-event coefficients are large and positive, with the strongest response occurring in the first month after the hurricane, indicating an immediate and economically meaningful tightening of credit pricing for financial firms.

Pre-event coefficients are generally small and statistically indistinguishable from zero, providing no evidence of differential pre-trends, although the estimates are less precise than in the full sample due to the smaller number of financial borrowers. Panel (B) shows that when the treatment group is expanded to include all exposed counties, the post-event increase in spreads remains positive but is somewhat attenuated relative to the high-exposure comparison in Panel (A). Overall, the dynamic patterns reinforce the conclusion that lenders reprice credit risk more aggressively for financial firms following major hurricane shocks.

Figure 2: Harvey Impact on Syndicate Loan Spread: Financial Borrowers



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The sample is restricted to financial borrowers, defined as firms with four-digit SIC codes between 6000–6499 and 6700–6799. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Non-financial borrowers. We next examine credit supply responses for non-financial firms, which are less directly exposed to funding market disruptions and balance-sheet spillovers. This comparison allows us to assess whether the tightening observed for financial borrowers reflects broad-based risk repricing or is concentrated among firms that are more closely tied to the financial system.

Table 4 reports difference-in-differences estimates for non-financial borrowers around Hurricane Harvey. In contrast to financial firms, we find no evidence of a post-hurricane increase in loan spreads for non-financial borrowers located in more exposed counties. Instead, adjustment occurs primarily along non-price margins. The number of lenders increases for exposed borrowers, while tranche amounts exhibit no robust or systematic response. These results indicate that, for non-financial firms, lenders respond to heightened hurricane risk by reconfiguring syndicate participation rather than tightening credit prices.

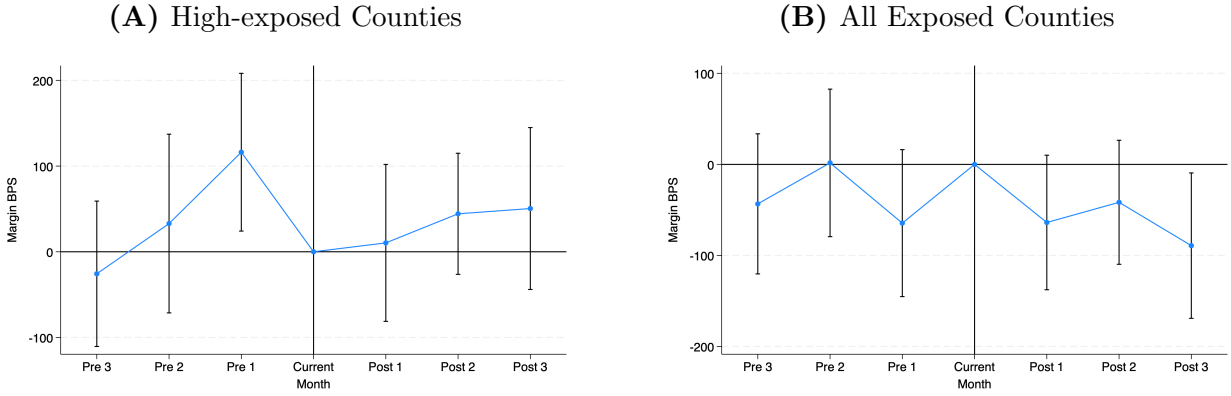
Table 4: Harvey Impact on Syndicated Loan Terms: Non-Financial Borrowers

	(1) Margin BPS	(2) No. Lenders	(3) Ln Amount	(4) Margin BPS	(5) No. Lenders	(6) Ln Amount
DID	6.044	1.227**	0.011	-35.730**	0.942*	0.119
	(17.40)	(0.58)	(0.16)	(17.92)	(0.53)	(0.12)
Tenor Maturity	1.164***	0.044***	0.015***	1.259***	0.039***	0.015***
	(0.17)	(0.00)	(0.00)	(0.18)	(0.00)	(0.00)
Observations	4348	4348	4348	6031	6031	6031
R^2	0.690	0.763	0.687	0.674	0.751	0.691

Notes: This table reports Difference-in-Differences estimates of the impact of Hurricane Harvey using borrower exposure. The sample is restricted to *non-financial borrowers*, defined as firms outside four-digit SIC codes 6000–6990. Columns (1)–(3) compare borrowers located in high-exposure counties (Q4) to the control group (Q1). Columns (4)–(6) expand the treatment group to all exposed counties (Q2–Q4). Standard errors are clustered at the lender level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 presents dynamic event-study estimates of the effect of Hurricane Harvey on syndicated loan spreads for non-financial borrowers. In contrast to financial firms, the estimated coefficients exhibit no clear or persistent increase in loan spreads following the hurricane for more exposed counties. Pre-event coefficients are noisy and do not display a stable pre-trend, and post-event estimates are imprecise and centered close to zero. Overall, the figure indicates that lenders do not systematically reprice credit for non-financial borrowers through interest rate spreads in response to heightened hurricane risk, consistent with the static results in Table 4.

Figure 3: Harvey Impact on Syndicated Loan Spread: Non-Financial Borrowers



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The sample is restricted to non-financial borrowers, defined as firms excluding those with four-digit SIC codes between 6000 and 6999. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Taken together, the evidence from Hurricane Harvey indicates that lenders respond to heightened physical climate risk primarily through credit pricing, and that this response is highly heterogeneous across borrower types. For the full sample, loan spreads increase and credit supply contracts for borrowers located in counties with greater historical hurricane exposure, even when those counties are not directly hit by the disaster. This effect is particularly pronounced for financial borrowers, who experience large and immediate increases in borrowing costs following the hurricane, consistent with lenders reassessing risk in sectors that are more exposed through interconnected balance sheets and local economic linkages. In contrast, for non-financial borrowers, we find little evidence of systematic repricing through loan spreads, with adjustments occurring mainly along non-price margins. Overall, the Harvey results suggest that major hurricanes can trigger a reassessment of climate-related risk by lenders, with the strongest effects concentrated among borrowers for whom local shocks are most likely to propagate through the financial system.

4.2 Harvey Hurricane: Lender Perspective

We now shift to the lender perspective to examine how hurricane risk is transmitted and shared through financial intermediaries' balance sheets. This analysis exploits cross-lender variation in exposure to hurricane-prone areas, even when lenders originate credit to borrowers in unaffected locations. We consider two complementary channels: exposure through lenders' deposit footprints, capturing funding-side vulnerability, and exposure through existing syndicated loan portfolios, capturing asset-side risk. We also compare bank and nonbank lenders to assess how differences in intermediary business models shape adjustment margins, showing that nonbanks act as partial stabilizers by expanding credit along non-price margins in exposed regions.

Risk Sharing in Deposit Channel (bank lenders) Table 5 examines how banks' exposure to hurricane risk through their deposit footprint affects credit supply following Hurricane Harvey. The table reports difference-in-differences estimates where treatment is defined at the lender level based on deposit-weighted exposure to historically hurricane-prone counties. Columns (1)–(3) focus on loans originated in risky but unaffected locations—counties with historical hurricane exposure that did not experience a hurricane in the year prior to Harvey—while columns (4)–(6) restrict attention to loans originated in historically safe counties.

In risky locations, lenders with higher deposit exposure to hurricane risk charge significantly higher interest rate spreads and extend loans with shorter maturities, consistent with a tightening of credit conditions driven by funding-side risk. By contrast, in safe locations, more exposed lenders offer lower interest rate spreads and larger loan amounts, indicating a reallocation of lending away from hurricane-prone areas. Taken together, the results provide evidence of risk transmission and risk sharing through the deposit channel, whereby banks adjust credit pricing and allocation across space in response to localized climate shocks.

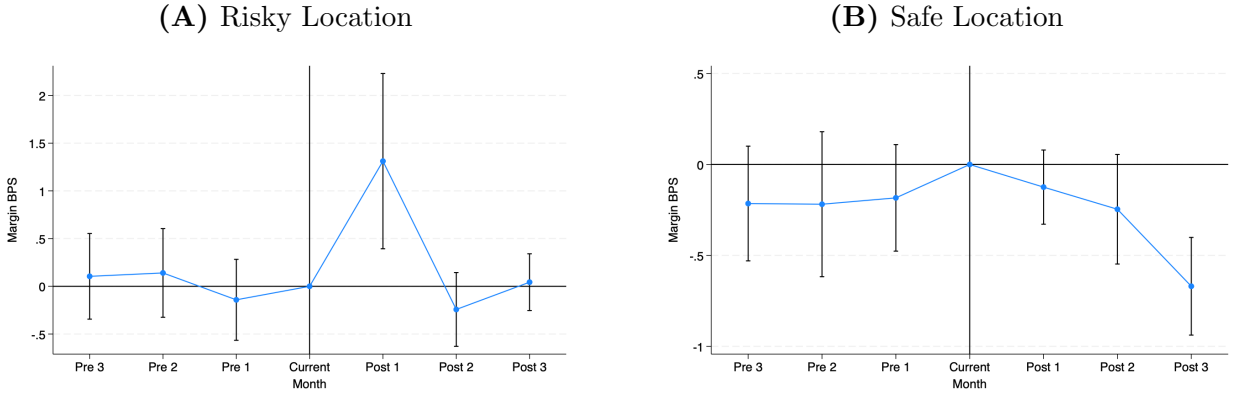
Table 5: Risk Sharing/Transmission through Deposit Channel

	(1) Margin BPS	(2) Ln Amount	(3) Maturity	(4) Margin BPS	(5) Ln Amount	(6) Maturity
DID	0.398***	0.001**	-0.038***	-0.212***	0.001***	-0.003
	(0.11)	(0.00)	(0.01)	(0.06)	(0.00)	(0.01)
Maturity	1.531***	0.007***		1.277***	0.016***	
	(0.25)	(0.00)		(0.19)	(0.00)	
Observations	2863	2863	2863	10825	10825	10825
R^2	0.793	0.810	0.728	0.799	0.773	0.654

Notes: This table reports Difference-in-Differences results for Hurricane Harvey from the lender perspective using deposit-based exposure to hurricane risk. Columns (1)–(3) focus on loans originated in historically hurricane-prone counties that did not experience a hurricane in the year prior to the event, while columns (4)–(6) focus on loans originated in historically safe counties that have never experienced hurricanes. Standard errors are clustered at the lender level and reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4 presents event-study estimates of syndicated loan spreads around Hurricane Harvey based on lenders' deposit exposure to hurricane risk. In Panel (A), pre-event coefficients are statistically indistinguishable from zero, supporting the parallel trends assumption, and loan spreads increase significantly in the first month following the hurricane in risky but unaffected locations. In Panel (B), pre-event coefficients also support parallel trends; however, loan spreads in safe locations decline more gradually and become statistically significant only three months after the event, consistent with delayed risk-sharing through the deposit channel.

Figure 4: Risk Sharing in Syndicated Loan Spread through Deposit



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Risk Sharing in Asset Channel (all lenders) Table 6 examines how lenders' exposure to hurricane risk through their existing syndicated loan portfolios affects credit supply following Hurricane Harvey. The table reports difference-in-differences estimates where treatment is defined at the lender level based on loan-weighted exposure to historically hurricane-prone counties. In risky locations, reported in columns (1)-(3), lenders with higher loan-portfolio exposure to hurricane risk charge significantly higher interest rate spreads and extend smaller loan amounts, consistent with tighter credit conditions driven by asset-side risk. By contrast, in safe locations, reported in columns (4)–(6), the estimates point to lower interest rate spreads and larger tranche amounts, although these effects are less precisely estimated. Overall, the results indicate that hurricane risk propagates through lenders' balance sheets not only via funding channels but also through existing credit portfolios, leading to a reallocation of lending away from hurricane-prone areas and toward safer locations.

Table 6: Risk Sharing/Transmission through Asset Channel

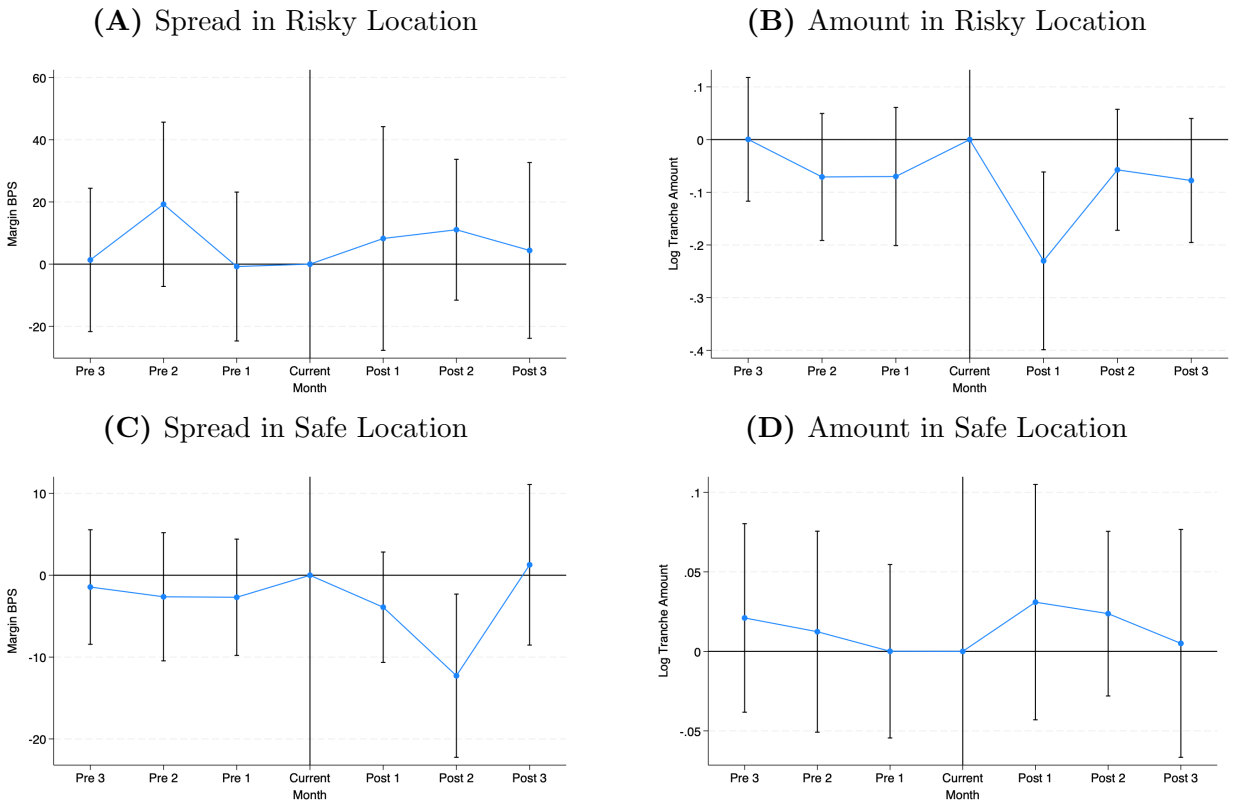
	(1) Margin BPS	(2) Ln Amount	(3) Maturity	(4) Margin BPS	(5) Ln Amount	(6) Maturity
DID4	12.536**	-0.042**	-0.541	-4.595	0.007	-0.547
	(5.82)	(0.02)	(1.11)	(3.47)	(0.03)	(0.65)
Maturity	1.437***	0.006***		1.286***	0.017***	
	(0.28)	(0.00)		(0.21)	(0.00)	
Observations	2294	2294	2294	8963	8963	8963
r2	0.759	0.791	0.723	0.765	0.749	0.643

Notes: This table reports Difference-in-Differences results for Hurricane Harvey from the lender perspective using loan-based exposure to hurricane risk. Columns (1)–(3) focus on loans originated in historically hurricane-prone counties that did not experience a hurricane in the year prior to the event, while columns (4)–(6) focus on loans originated in historically safe counties that have never experienced hurricanes. Standard errors are clustered at the lender level and reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5 extends the asset-channel results in Table 6 by tracing the dynamic adjustment of syndicated loan spreads and amounts around Hurricane Harvey. Panels (A) and (B) focus on risky but unaffected locations. In these locations, pre-event coefficients are small and statistically indistinguishable from zero, supporting the parallel trends assumption. Following the hurricane, tranche amounts decline sharply and significantly in the first post-event month, while spread responses are less precisely estimated, indicating that lenders primarily adjust along the quantity margin when facing heightened asset-side risk.

Panels (C) and (D) report estimates for historically safe locations. In contrast, the post-event adjustment in these locations occurs mainly through pricing: loan spreads decline in the post-event period, while changes in loan amounts are small and not statistically significant. This asymmetric response is consistent with risk-sharing behavior, whereby lenders reallocate credit toward safer areas and offer more favorable pricing to diversify risk away from hurricane-prone regions. Overall, the figure corroborates the table evidence that hurricane risk propagates through lenders' existing loan portfolios, generating both risk transmission in exposed areas and risk sharing across space.

Figure 5: Risk Sharing in Syndicated Loan Spread and Amount



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Table 7 examines how nonbank lenders adjust credit supply following Hurricane Harvey, relative to bank lenders, using a difference-in-differences framework. Columns (1)–(3) focus on loans originated in historically hurricane-prone counties that experienced a hurricane in the year prior to the event, while Columns (4)–(6) consider loans originated in historically safe counties.

In hurricane-prone locations, nonbank lenders do not significantly increase loan spreads following the hurricane. Instead, adjustment occurs primarily along non-price margins: loan amounts increase and maturities lengthen relative to bank lenders. This pattern suggests that nonbanks partially absorb heightened credit demand in risky areas, expanding credit

supply rather than tightening pricing. In contrast, in historically safe counties, nonbank lenders exhibit no statistically significant response across pricing, loan size, or maturity. This absence of adjustment indicates that nonbank lending does not play a major role in reallocating credit toward safer locations following climate shocks.

Taken together, the results suggest that nonbank lenders act as partial shock absorbers in exposed regions, mitigating but not fully offsetting the tightening of bank credit in the aftermath of major climate events.

Table 7: Role of Nonbanks

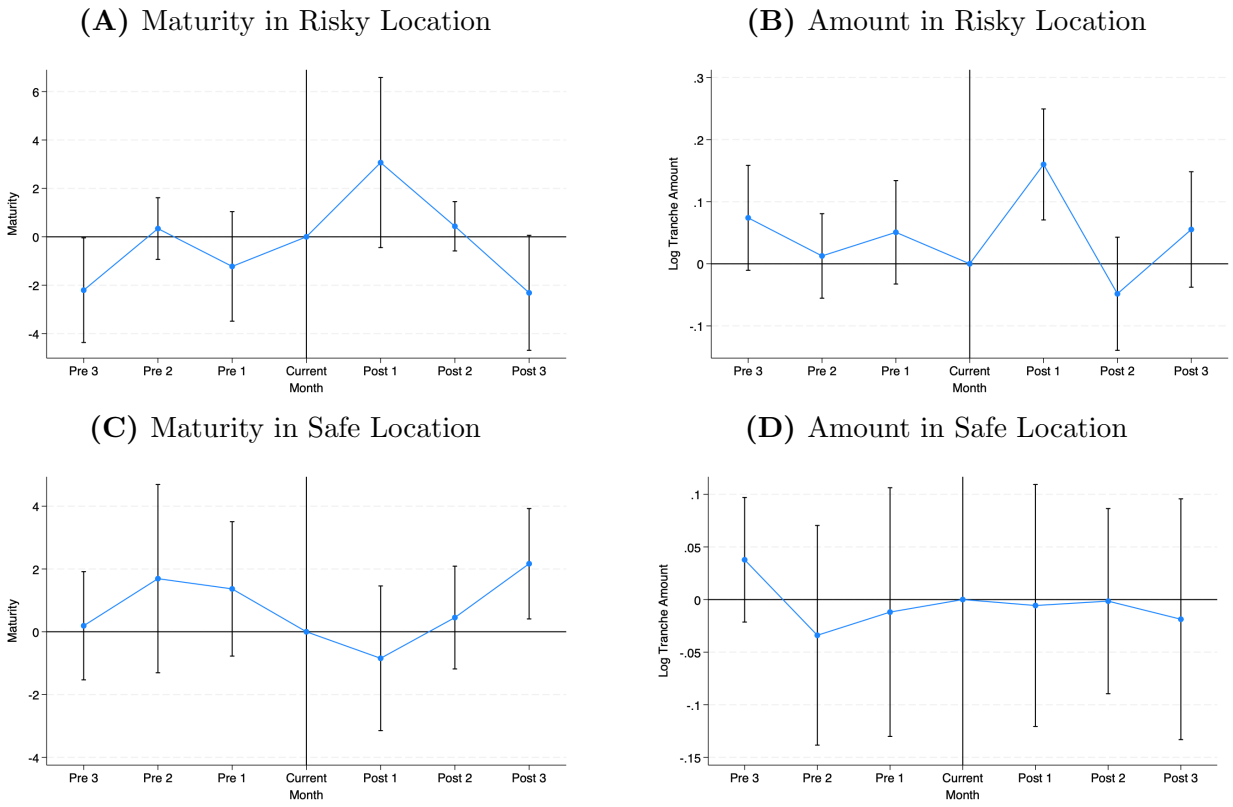
	(1) Margin BPS	(2) Ln Amount	(3) Maturity	(4) Margin BPS	(5) Ln Amount	(6) Maturity
DID	-10.608	0.072**	1.727*	7.923	-0.009	-0.195
	(9.24)	(0.03)	(0.91)	(8.02)	(0.03)	(0.74)
Maturity	1.283***	0.009***		1.277***	0.016***	
	(0.17)	(0.00)		(0.19)	(0.00)	
Observations	5782	5782	5782	10825	10825	10825
r2	0.792	0.760	0.666	0.799	0.773	0.654

Notes: This table reports Difference-in-Differences results for Hurricane Harvey by comparing the outcomes of the nonbank lenders and bank lenders. Columns (1)–(3) focus on loans originated in historically hurricane-prone counties that experienced a hurricane in the year prior to the event, while columns (4)–(6) focus on loans originated in historically safe counties that have never experienced hurricanes. Standard errors are clustered at the lender level and reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 6 presents event-study estimates of nonbank lending responses around Hurricane Harvey. In risky locations, nonbank lenders extend credit primarily along non-price margins, increasing both loan maturities and loan amounts in the immediate post-event period. These responses suggest that nonbanks partially accommodate heightened credit demand or substitute for bank credit following climate shocks. In contrast, in historically safe locations, nonbank lending exhibits no systematic adjustment in either maturity or loan size. Overall, the dynamic patterns indicate that nonbank lenders play a stabilizing role in exposed regions, smoothing credit supply without driving broad reallocation across locations.

Figure 6: Non Banks as Stabilizer



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The outcome variable is the syndicated loan maturity and log amount at the tranche level, measured as the month and percentage change. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

5 Conclusion

This paper studies how physical climate risk is priced and transmitted in U.S. credit markets by examining lender and borrower responses to major hurricanes, with a primary focus on Hurricane Harvey. Exploiting sharp disaster events as information shocks and combining borrower- and lender-level exposure measures based on historical hurricane risk, we show that lenders adjust credit pricing and allocation not only in directly affected areas but also in locations with greater ex ante vulnerability to physical climate risk. By restricting

attention to borrowers and lenders in counties that were not directly hit by the disaster, our empirical design isolates changes in perceived climate risk from the effects of realized physical damage.

From the borrower perspective, we document a pronounced tightening of credit conditions following Hurricane Harvey for borrowers located in more hurricane-exposed counties. Loan spreads increase sharply and persistently even in the absence of local damage, and event-study estimates confirm that these effects emerge immediately after the hurricane with no evidence of differential pre-trends. These patterns indicate that lenders update their assessment of climate-related risk in a forward-looking manner. To assess how these responses have evolved over time, we contrast the Harvey results with evidence from Hurricane Katrina (2005) and Hurricane Ian (2022). While Katrina primarily induces quantity adjustments with little repricing, both Harvey and Ian generate sizable increases in loan spreads, pointing to a growing role of physical climate risk in credit pricing. Consistent with this interpretation, we also find similar post-event increases in interest rates in SBA 7(a) loans, suggesting that heightened climate risk perceptions transmit to small business credit markets as well.

Credit supply responses are highly heterogeneous across borrower types. Financial firms experience large and immediate increases in borrowing costs following hurricanes, accompanied by contractions in loan size and syndicate participation. In contrast, non-financial borrowers do not face systematic repricing through interest rate spreads; instead, lenders adjust primarily along non-price margins, such as syndicate composition. This heterogeneity suggests that physical climate risk disproportionately affects borrowers that are more closely tied to the financial system, consistent with balance-sheet spillovers and interconnectedness among financial institutions.

From the lender perspective, we provide direct evidence on how hurricane risk propagates through financial intermediaries' balance sheets. Using deposit-based exposure, we show that banks with greater funding-side exposure to hurricane-prone areas tighten credit terms in risky locations while reallocating lending toward safer regions, consistent with risk sharing through the deposit channel. Using loan-portfolio exposure, we find similar patterns along the asset channel: lenders more exposed to hurricane risk through existing loans contract credit in risky areas and offer more favorable terms in safe locations. Dynamic evidence indicates that these adjustments occur through both pricing and quantity margins, revealing how localized climate shocks generate spatial reallocation of credit. Importantly,

we also document a distinct role for nonbank lenders. Relative to banks, nonbank lenders do not significantly reprice credit following hurricanes and instead adjust primarily along non-price margins. In exposed regions, nonbanks expand loan amounts and maturities, partially absorbing increased credit demand when bank lending tightens, while exhibiting little systematic response in historically safe locations. These findings suggest that nonbank lenders act as partial stabilizers in the aftermath of climate shocks, mitigating—but not fully offsetting—the contraction in bank-supplied credit.

Taken together, our findings have important implications for climate stress testing and financial stability. First, they show that physical climate risk is already priced in credit markets in a forward-looking manner, even absent realized losses. Second, the strong responses for financial borrowers and the balance-sheet channels documented from the lender perspective suggest that climate shocks can propagate endogenously through the financial system, amplifying their macro-financial consequences. Third, the coexistence of risk transmission and risk sharing across locations highlights the need to consider both borrower- and lender-side exposures when assessing climate-related financial risks.

More broadly, this paper provides evidence that physical climate risk is a persistent, location-specific factor shaping credit market outcomes. As climate change increases the frequency and severity of extreme weather events, understanding how financial institutions price, transmit, and redistribute these risks will be central to effective regulation and stress-testing frameworks. As a next step, we aim to move beyond reduced-form evidence and develop a structural framework to study how climate risk propagates through the financial system. Such a model would allow us to assess whether climate risk is underpriced, overpriced, or efficiently priced, and to quantify the channels through which localized climate shocks generate broader financial and macroeconomic effects. We view the integration of tools from macroeconomics, finance, and spatial economics as a promising avenue for advancing the study of climate risk and financial stability.

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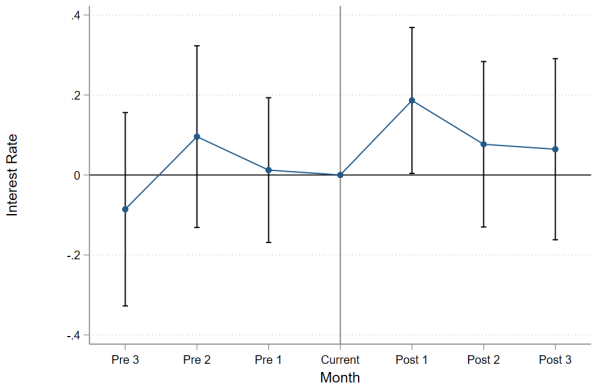
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6 Appendix

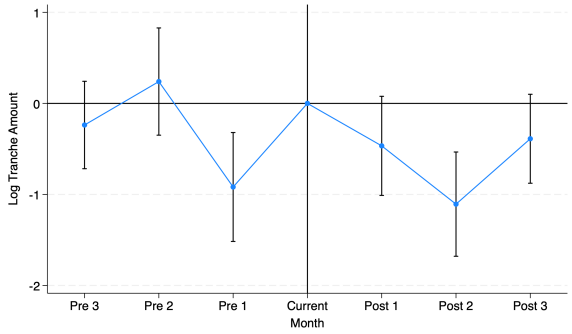
Figure 7: Interest Rate for 7a Loan - Harvey



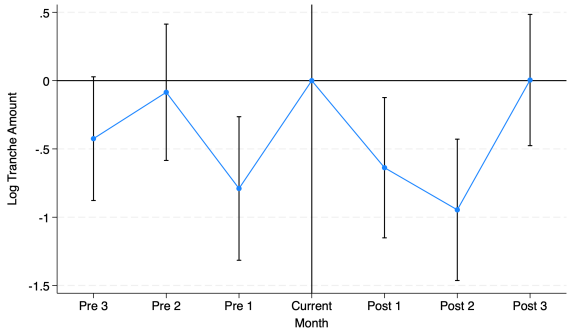
Notes: This figure presents event-study estimates of the effect of Hurricane Harvey on interest rates for SBA 7(a) loans. The estimates are obtained from a difference-in-differences specification that compares loans issued by lenders with higher exposure to hurricane risk to those with low exposure lenders, before and after the hurricane. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event.Vertical bars denote 95% confidence intervals.

Figure 8: Harvey Impact on Syndicate Loan Tranche Amount

(A) High-exposed Counties



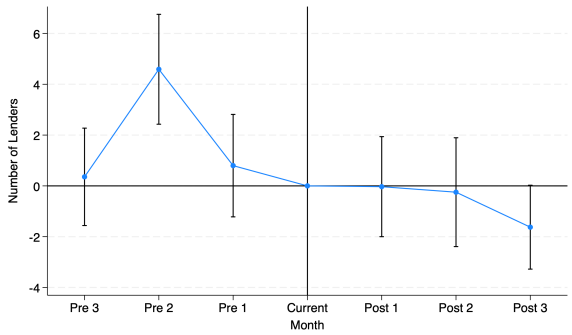
(B) All Exposed Counties



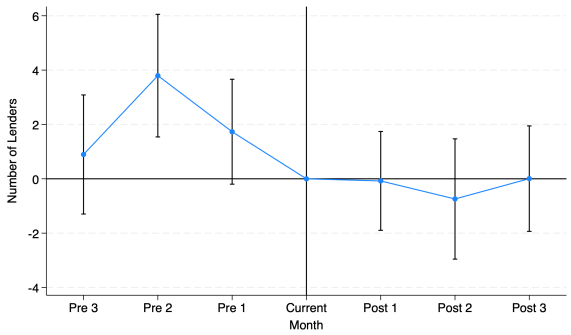
Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The sample includes all borrowers. The outcome variable is the syndicated loan tranche amount, measured in logarithms. Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Figure 9: Harvey Impact on Syndicate Number of Lenders

(A) High-exposed Counties



(B) All Exposed Counties



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The sample includes all borrowers. The outcome variable is the number of lenders participating in the syndicated loan. Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

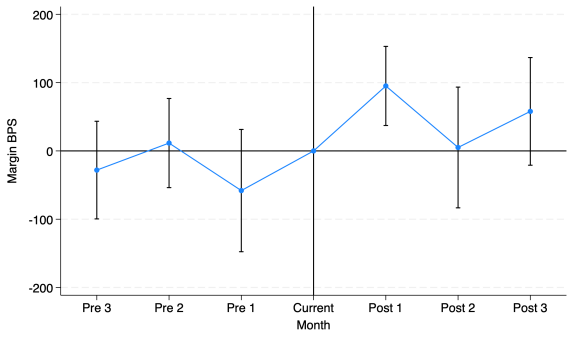
Table 8: Ian Impact on Syndicated Loan Outcomes

	(1) Margin BPS	(2) No. Lenders	(3) Ln Amount	(4) Margin BPS	(5) No. Lenders	(6) Ln Amount
DID	82.165***	1.545*	0.310	48.293***	1.392**	0.424**
	(14.48)	(0.89)	(0.20)	(13.35)	(0.69)	(0.20)
Tenor Maturity	1.411***	0.051***	0.010***	1.329***	0.080***	0.008***
	(0.23)	(0.01)	(0.00)	(0.16)	(0.01)	(0.00)
Observations	2225	2225	2225	3488	3488	3488
R^2	0.903	0.767	0.718	0.881	0.747	0.698

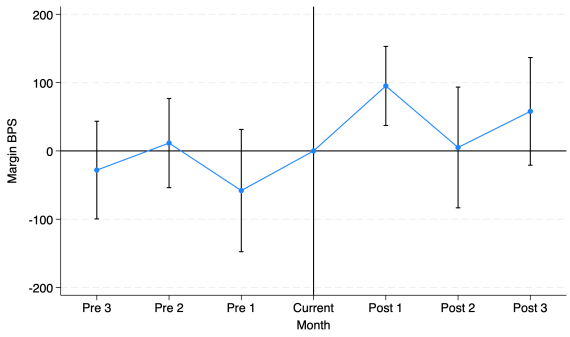
Notes: This table reports the Difference-in-Differences results for Hurricane Ian using all borrowers. Columns (1)-(3) compare high-exposure counties (Q4) to the control group. Columns (4)-(6) expand the treatment to all exposed counties (Q2-Q4). Standard errors are clustered at the lender level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 10: Ian Impact on Syndicate Loan Spread

(A) High-exposed Counties



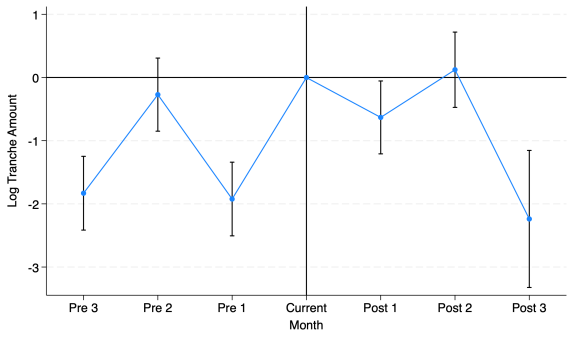
(B) All Exposed Counties



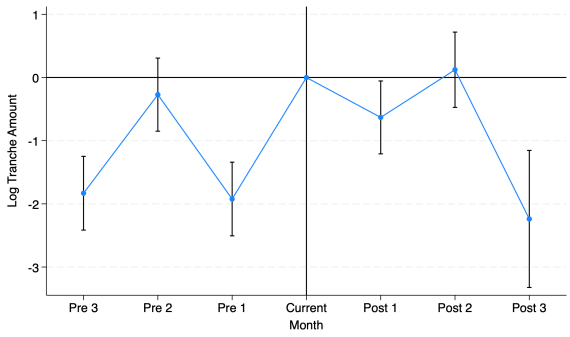
Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Ian. The sample includes all borrowers. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Figure 11: Ian Impact on Syndicate Loan Tranche Amount

(A) High-exposed Counties

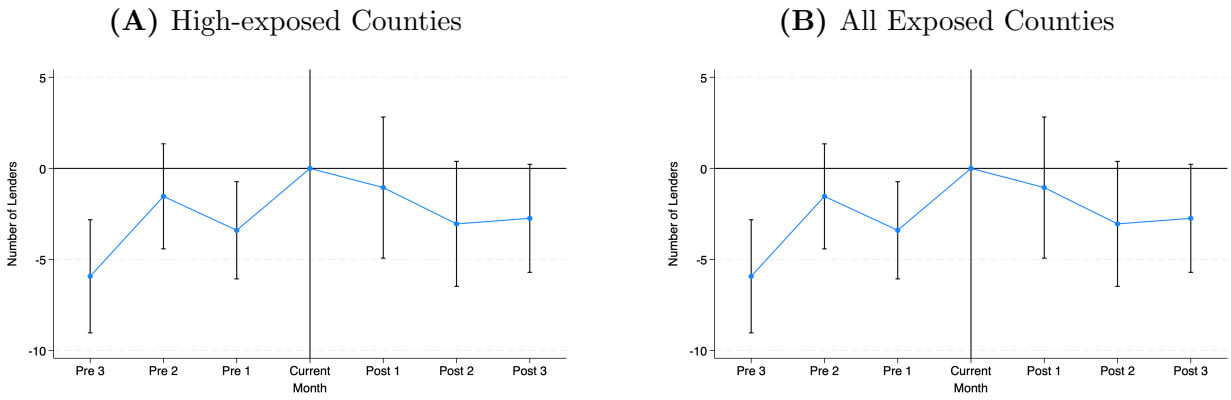


(B) All Exposed Counties



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Ian. The sample includes all borrowers. The outcome variable is the syndicated loan tranche amount, measured in logarithms. Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event.

Figure 12: Ian Impact on Syndicate Number of Lenders



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Ian. The sample includes all borrowers. The outcome variable is the number of lenders participating in the syndicated loan. Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event.

Table 9: Katrina Impact on Syndicated Loan Outcomes

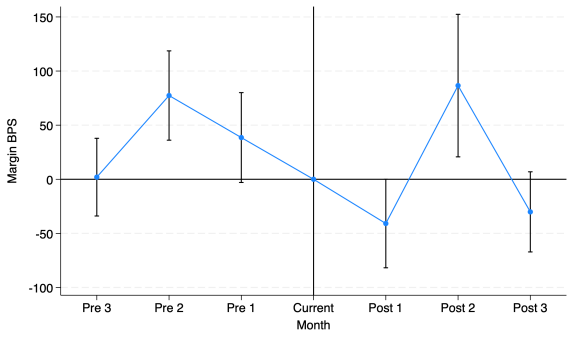
	(1) Margin BPS	(2) No. Lenders	(3) Ln Amount	(4) Margin BPS	(5) No. Lenders	(6) Ln Amount
DID	-20.463	-3.259***	-0.561***			
	(15.01)	(1.15)	(0.20)			
DID3				-26.023***	5.792***	-0.064
				(6.74)	(0.82)	(0.08)
Tenor Maturity	0.236**	0.035***	0.004***	-0.068	0.038***	0.005***
	(0.10)	(0.01)	(0.00)	(0.08)	(0.01)	(0.00)
Observations	8,388	8,388	8,305	14,080	14,080	13,952
R^2	0.606	0.786	0.588	0.578	0.828	0.558

Notes: This table reports the results of the Difference-in-Differences analysis for Hurricane Katrina. Columns (1)-(3) compare high-exposure (Q4) to low-exposure (Q1) counties. Columns (4)-(6) compare any-exposure (Q2-Q4) to the control group. Standard errors are clustered at the lender level and reported in parentheses.

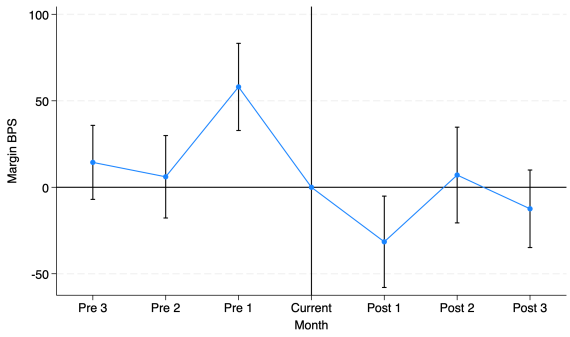
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 13: Katrina Impact on Syndicate Loan Spread

(A) High-exposed Counties



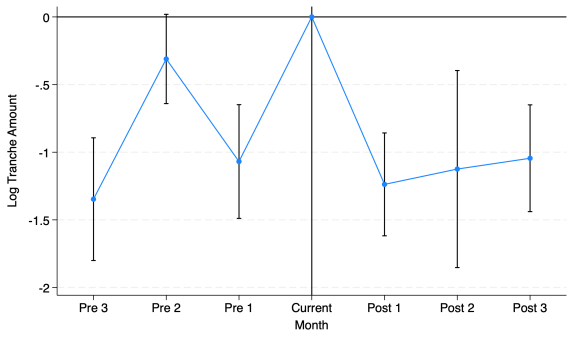
(B) All Exposed Counties



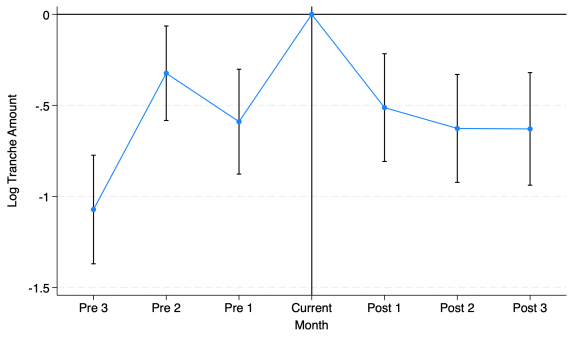
Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Katrina. The sample includes all borrowers. The outcome variable is the syndicated loan spread at the tranche level, measured as the margin over the benchmark rate (basis points). Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event. Vertical bars denote 95% confidence intervals.

Figure 14: Katrina Impact on Syndicate Loan Tranche Amount

(A) High-exposed Counties



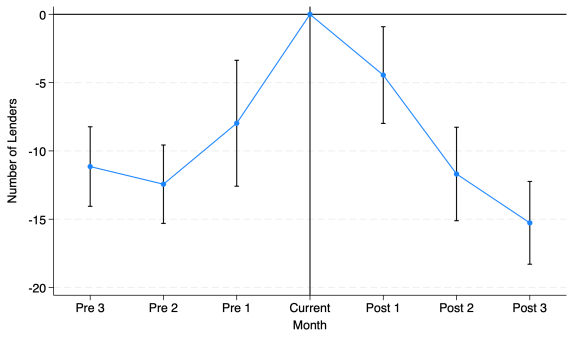
(B) All Exposed Counties



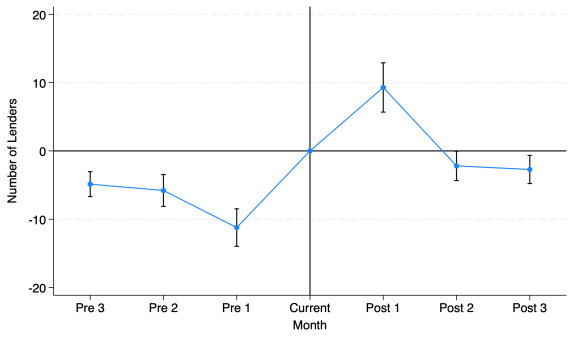
Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Katrina. The sample includes all borrowers. The outcome variable is the syndicated loan tranche amount, measured in logarithms. Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event.

Figure 15: Katrina Impact on Syndicate Number of Lenders

(A) High-exposed Counties



(B) All Exposed Counties



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Katrina. The sample includes all borrowers. The outcome variable is the number of lenders participating in the syndicated loan. Borrower exposure is measured using county-level hurricane property damage based on the borrower's location. The event time is defined relative to the hurricane month ($t = 0$). Coefficients are reported for the three months before and after the hurricane, with the omitted category being the month immediately prior to the event.