Pricing and Transmission of Climate Risk in Corporate Loans *

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Abstract

We study how localized climate shocks transmit through financial intermediaries to affect credit conditions beyond directly impacted areas. Using Hurricane Harvey and U.S. syndicated loan data, we exploit variation in borrowers' geographic exposure and lenders' portfolio concentration across hurricane-prone counties to identify the indirect transmission of climate risk. We find that loan spreads increase by 0.65% for borrowers in high-exposure but unaffected counties following Harvey, alongside reductions in loan amounts, syndicate size, and maturity. On the lender side, responses differ sharply by intermediary type. Exposed banks tighten credit in risky areas and reallocate toward safer locations, while nonbank lenders expand credit in those same areas, partially offsetting the bank retreat. These results show that climate shocks do not remain local but are re-priced and redistributed through financial intermediaries. The transmission of climate risk depends on the identity of the marginal lender and the geographic structure of intermediary portfolios, with important implications for the distribution of risk in the financial system.

JEL Classification: G21, G23, Q51, Q54

Keywords: Banks, Nonbanks, Loan pricing, Natural disasters, Climate risk transmission

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1 Introduction

Local climate disasters are increasingly severe and economically consequential shocks. In early 2026 alone, extreme weather events struck simultaneously across regions, including severe cold spells in the United States, devastating floods in Southern Africa, and large-scale wildfires in Chile. These events highlight that climate risk is no longer a distant concern but an immediate and recurring source of economic disruption. Hurricanes, floods, and wildfires destroy physical capital, disrupt production, and depress local demand, generating large and persistent economic losses (e.g., Garmaise and Moskowitz, 2009; Blickle et al., 2021; Billings et al., 2022; Collier et al., 2024; Gallagher and Hartley, 2025). Over the last decade alone, the United States has experienced nearly 190 billion-dollar weather and climate disasters, with total damages exceeding $1.4 trillion, and these costs continue to rise (NOAA, 2025).

Despite their local nature, these shocks need not remain geographically contained. Modern credit markets are highly integrated, allowing local disruptions to propagate through financial intermediaries, investors, and lending networks (e.g., Dessaint and Matray, 2017; Cortés and Strahan, 2017; Koetter et al., 2020; Correa et al., 2025). These concerns are reflected in the work of the Network for Greening the Financial System (NGFS), whose more than 130 member central banks and supervisors now routinely use climate scenarios for stress testing. However, micro-level evidence on how climate shocks transmit through credit markets, and on who ultimately bears the redistributed risk, remains limited. These issues are further amplified by the rapid growth of nonbank financial intermediaries, which increasingly supply credit outside the traditional banking sector and may propagate shocks through leverage, liquidity mismatches, and strong interconnections with banks (Aramonte et al., 2021; IMF, 2023; Financial Stability Board, 2025). A central question therefore remains: how are local physical climate shocks priced and transmitted through credit markets, and to what extent does the identity of the marginal lender shape this process?

This paper addresses these questions using Hurricane Harvey and U.S. syndicated loan data. We exploit variation in borrowers' historical hurricane exposure across non-affected counties in a difference-in-differences design, comparing credit outcomes in high- and low-exposure counties that sustained no direct damage from the storm. By excluding FEMA-declared counties entirely, the design isolates the indirect transmission of climate risk through financial intermediaries rather than its direct local effects. We further exploit cross-lender

variation in portfolio concentration across hurricane-prone counties, using both deposit footprints and existing loan portfolios, to trace how intermediary-level exposure shapes pricing and allocation decisions for new loans in unaffected areas.

Our analysis distinguishes between two conceptually distinct channels through which disasters affect credit markets. The first is a borrower-risk channel, whereby disasters deteriorate local economic fundamentals such as expected cash flows and near-term default risk (Garmaise and Moskowitz, 2009; Koetter et al., 2020; Javadi and Masum, 2021; Correa et al., 2025). In this case, higher borrowing costs reflect a rational repricing of borrower risk, as lenders adjust contract terms to account for increased exposure in vulnerable locations. The second channel operates through financial intermediaries. When disasters occur, risk is aggregated on intermediary balance sheets, potentially tightening funding constraints and altering lenders' pricing and portfolio allocation decisions across all locations (Peek and Rosengren, 2000; Cortés and Strahan, 2017; Blickle et al., 2021). As a result, credit conditions may change even for borrowers not directly exposed to the disaster, reflecting shifts in the supply of credit rather than changes in borrower fundamentals (Khwaja and Mian, 2008). Disentangling these channels is critical for understanding whether disaster risk primarily reallocates credit locally or instead reshapes aggregate financial conditions. While loan pricing typically depends on borrower-specific risk, it may also reflect lender-side constraints (Jiménez et al., 2012; Ivashina and Scharfstein, 2010). When intermediaries face balance sheet stress, they may raise rates independently of borrower fundamentals (Siriwardane, 2019; Chava and Purnanandam, 2011).

We document three main findings. First, local disaster shocks increase borrowing costs well beyond the affected area. Loan spreads rise by approximately 66 basis points for borrowers in high-exposure but unaffected counties, roughly 25 percent above pre-event levels. At the same time, loan amounts, maturities, and syndicate participation all contract. These effects revert within the hurricane season window, consistent with lenders pricing near-term conditional risk rather than permanently reassessing long-run climate vulnerability.

Second, transmission operates through intermediary networks rather than borrower fundamentals. The repricing is concentrated among financial firms, which experience spread increases of approximately 110 basis points together with sharp contractions across all non-price margins, while non-financial firms are largely unaffected. This asymmetry rules out a broad deterioration in borrower creditworthiness and instead points to the financial system

itself as the amplifier of local climate shocks.

Third, lender identity is central to how climate risk is transmitted and redistributed. Banks and nonbanks respond to the same shock in opposite ways. Exposed banks reduce lending in risky locations and reallocate toward safer areas, consistent with portfolio rebalancing under capital and supervisory constraints. In contrast, nonbanks expand credit in those same risky regions, absorbing the climate risk that regulated intermediaries shed. This substitution implies that climate risk is not eliminated from the financial system but instead reallocated toward less regulated intermediaries. This reallocation may reduce short-run disruptions in credit supply but raises longer-run concerns about the concentration of correlated climate risk outside the traditional prudential perimeter. The concentration of effects in risky locations across both lender types is consistent with a belief-updating channel. Harvey acts as a signal that prompts lenders with concentrated exposures to reassess latent portfolio risk, rather than generating uniform tightening through direct balance sheet impairment.

Related Literature. This paper contributes to three strands of the literature. First, it relates to work documenting that physical climate risk is priced in financial markets and credit contracts (Bernstein et al., 2019; Ouazad and Kahn, 2019; Murfin and Spiegel, 2020; Goldsmith-Pinkham et al., 2023; Koetter et al., 2020; Javadi and Masum, 2021). Most closely related, Correa et al. (2025) show that loan spreads increase for at-risk but not directly affected borrowers following disasters, an identification strategy we share. Our contribution is to show that this repricing critically depends on the identity of the marginal lender: banks retrench along price, quantity, and maturity margins in exposed locations, while nonbanks expand their relative credit provision to those same locations, absorbing risk that regulated intermediaries shed.

Second, we contribute to the literature on bank geographic diversification and spatial credit spillovers (Goetz et al., 2016; Chu et al., 2020; Conlon et al., 2024). A canonical mechanism emphasizes internal capital markets, whereby banks reallocate lending across regions in response to shocks (Cortés and Strahan, 2017). We study a complementary channel: how lenders' geographically distributed portfolio exposures translate into differential repricing and credit allocation in integrated lending markets, including for borrowers in unaffected locations.

Third, we contribute to the literature on nonbank financial intermediation (Chernenko et al., 2022; Elliott et al., 2024; Aldasoro et al., 2025; Krainer et al., 2024). While this literature has focused largely on aggregate substitution between bank and market-based finance, we show that within the syndicated loan market, banks and nonbanks respond differently to the same disaster shock along price, quantity, and maturity margins, with important implications for the distribution and concentration of climate risk across the financial system.

Section 2 describes the data sources. Section 3 outlines the empirical identification strategy design used to estimate the effects of hurricane risk on credit markets. Section 4 presents the main empirical results. 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 allows us to compare the responses of nonbank and bank lenders to large physical climate shocks from both the borrower and lender perspectives.

2.1 Hurricane Exposure

We measure localized climate risk using the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which provides county–month records of natural disaster impacts including inflation-adjusted property and crop damage, event frequencies, and durations. We restrict attention to the "Hurricane and Tropical Storm" category to isolate large-scale, spatially concentrated shocks that are plausibly exogenous to local economic conditions.

Our estimation sample conditions on counties having experienced at least one hurricane or tropical storm since the inception of the SHELDUS record in 1960. This restriction ensures that comparisons are drawn from the "hurricane-prone universe" (regions where tropical cyclones represent a salient and recurring risk) rather than from geographically dissimilar areas with zero ex ante exposure.

Table 1 characterizes the distribution of hurricane exposure across the 947 historically

exposed counties for 2012–2021. The data exhibit extreme right-skewness: median cumulative property damage is roughly $5,459, while the mean exceeds $12.56 million, reflecting the dominance of rare catastrophic events. Average damage per event shows a similar pattern (mean $105,157; median $493).

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

Variable	Total	Mean	25th	50th (Median)	75th
Number of hurricanes (10y total)	6,909	7.30	0.00	1.00	5.00
10-year property damage per county (USD)	11.90 billion	12.56 million	0.00	5,458.60	245,779.46
Average property damage per event		105,156.52	0.43	492.64	3,437.76
Total property damage per capita (10y)		138.88	0.00	0.15	6.74

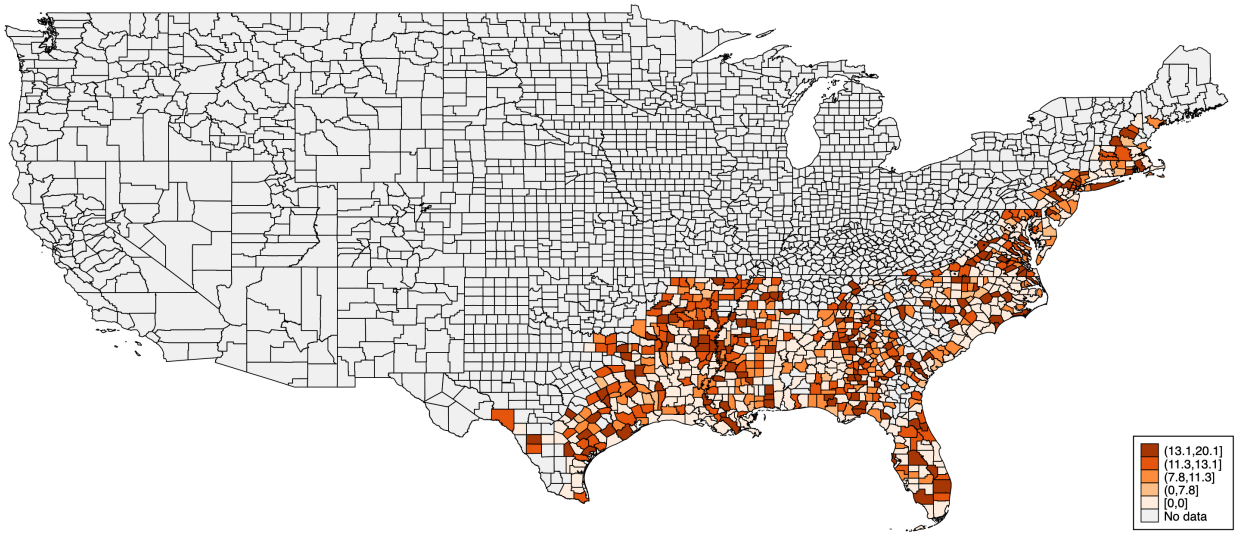
Notes: Hurricane exposure metrics for 947 U.S. counties, 2012–2021. Damage figures are in constant 2022 dollars. Per-capita values are per resident.

Exposure is concentrated along the Gulf and Atlantic Coasts, driven by the climatological steering patterns of the North Atlantic basin, principally the Bermuda High, a subtropical anticyclone that directs tropical cyclones toward the Eastern and Southeastern seaboard. Figure 1 maps the geographic distribution.

To identify major disaster events and their timing, we use Federal Emergency Management Agency (FEMA) disaster declarations issued under the Stafford Act.[1] Combining SHELDUS-based exposure with FEMA declarations enables us to separate long-run vulnerability from short-run realized shocks.

[1]Major disaster declarations are issued by the President following a gubernatorial request and authorize federal assistance for affected areas. We use them to identify the timing and geographic scope of major hurricanes, not to measure economic intensity.

Figure 1: Geographic Distribution of Hurricane Damage Exposure (2012–2021)



Notes: Color intensity corresponds to $\ln(1 + \text{Damage})$, ranging from 0 (no damage) to 20.1 (highest exposure). The log transformation accounts for the highly skewed distribution of disaster losses.

2.2 Syndicated Loans

We use syndicated loan data from DealScan (Refinitiv), which provide detailed 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, coordinated by one or more lead arrangers. The unit of observation is a loan tranche,a specific credit facility within a loan agreement,for which we observe the spread over the benchmark rate, tranche amount, maturity, loan type, and the composition of the lending syndicate.[2] We assign each tranche to the borrower's county using ZIP code–county crosswalks, restrict to U.S. borrowers with complete pricing and contract information, and complement the syndicated loan analysis with SBA 7(a) loan data to capture credit outcomes for small firms.[3]

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

[3]SBA 7(a) loans are government-guaranteed loans originated by banks and nonbank lenders to small businesses that typically lack access to syndicated credit markets. The program provides information on loan terms, interest rates, amounts, maturity, lender identity, and borrower location.

2.2.1 Sample Construction

Our analysis centers on a six-month window around Hurricane Harvey[4] (August 2017). The sample includes 913 unique borrowers, 634 lenders (banks and nonbanks), 943 deals, and 2,110 tranches. Because each tranche is funded by multiple lenders, this expands to 11,578 tranche–lender relationships; accounting for amendments over the sample window yields 19,830 tranche–lender–borrower observations. For the borrower perspective, we restrict to loans in hurricane-prone counties excluding directly affected areas, yielding approximately 8,800 observations.

2.2.2 Loan Characteristics

Table 2 reports sample composition by loan type and purpose. Term loans account for 56.64% of unique tranches and revolvers for 37.11%; the distribution is more balanced at the observation level (51.07% and 44.46%, respectively), reflecting larger syndicates on revolving facilities. General-purpose loans constitute the majority of the sample (53.51% of tranches, 63.35% of observations), followed by acquisition financing (16.64%) and leveraged buyouts (8.25%).

Table 3 describes observation structure: 61.01% correspond to amended tranches rather than original issuances.

[4]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 credit conditions respond to perceived physical climate risk.

Table 2: Sample Composition of DealScan Loan Records

	Tranche Level (Unique)			Tranche–Lender–Borrower Level		
	Count	(%)	Cum. (%)	Count	(%)	Cum. (%)
Panel A: Tranche Loan Type						
Term Loan	1,195	56.64	56.64	10,127	51.07	51.07
Revolver	783	37.11	93.75	8,816	44.46	95.53
Other Types	132	6.26	100.00	887	4.47	100.00
Total	**2,110**	**100**		**19,830**	**100**	
Panel B: Primary Loan Purpose						
General Purpose	1,129	53.51	53.51	12,560	63.35	63.35
Acquisition	351	16.64	70.15	1,916	9.66	73.01
Leveraged Buyout	174	8.25	78.40	1,540	7.77	80.78
Takeover	137	6.49	84.89	1,533	7.73	88.51
Dividend Recapitalization	104	4.93	89.82	479	2.42	90.93
Real Estate Loan	85	4.03	93.85	426	2.15	93.08
Other Purposes	130	6.16	100.00	1,376	6.94	100.00
Total	**2,110**	**100**		**19,830**	**100**	

Notes: Sample composition within ±3 months of Hurricane Harvey. "Other Types" includes bridge loans, letters of credit, and minor facilities. "Other Purposes" aggregates capital expenditures, DIP financing, exit financing, mergers, project finance, recapitalizations, spinoffs, stock repurchases, sponsored buyouts, and working capital.

Table 3: Composition of Tranche–Lender–Borrower Observations

	Count	(%)	Cum. (%)
Loan Status			
Original Tranches	7,731	38.99	38.99
Amended Tranches	12,099	61.01	100.00
Total	**19,830**	**100**	

Notes: Each observation is a lender's participation in a tranche at a given point in time. Amended tranches generate repeated observations over the sample window.

2.2.3 Lender Classification

Table 4 reports the distribution of lender types.[5] Banks account for 74.13% of unique lenders and 73.12% of observations, split between U.S. banks (41.80% of lenders, 49.96% of observations) and foreign banks (32.33%, 23.16%). Among nonbanks, investment banks are the largest subcategory (7.26% of lenders, 15.31% of observations), followed by debt investment funds (8.04%, 5.81%) and asset managers (5.05%, 3.98%).

Table 4: Sample Composition of Lender Type

	Unique Lenders			Tranche–Lender–Borrower		
Lender Type	Freq.	(%)	Cum.	Freq.	(%)	Cum.
Banks						
US Bank	265	41.80	41.80	9,908	49.96	49.96
Foreign Bank	205	32.33	74.13	4,592	23.16	73.12
Total Banks	**470**	**74.13**		**14,500**	**73.12**	
Non-Banks						
Investment Bank	46	7.26	81.39	3,036	15.31	88.43
Debt Investment Fund	51	8.04	89.43	1,153	5.81	94.24
Asset Management	32	5.05	94.48	790	3.98	98.22
Nonbank Credit Institution	24	3.79	98.27	321	1.62	99.84
Nonfinancial Company	4	0.63	98.90	12	0.06	99.90
Insurance	5	0.79	99.69	9	0.05	99.95
Real Estate Investment	2	0.32	100.0	9	0.05	100.0
Total Non-Banks	**164**	**25.87**		**5,330**	**26.88**	
Total	**634**	**100**		**19,830**	**100**	

Notes: Distribution of lender types in the Harvey sample. Each lender may appear multiple times across tranches and amendments. Banks comprise U.S. and foreign commercial banks; nonbanks include investment banks, debt funds, asset managers, and other categories as shown.

[5]Classification follows Aldasoro et al. (2025) with supplementary manual procedures. Several investment banks grouped as banks by DealScan are reclassified as nonbanks (e.g., Macquarie, RBC Capital Markets, Nomura). Lenders with SIC 6211 classified as banks are reassigned following Lim et al. (2014). Remaining ambiguous cases are resolved by searching for commercial bank identifiers across names, activity descriptions, and multilingual variants (*banca*, *banco*, *banque*).

2.2.4 Borrower Composition

Table 5 reports borrower distribution by industry. Corporates account for 82.80% of unique borrowers (77.68% of observations), followed by nonbank financial firms (9.64%, 12.76%) and utilities (5.37%, 5.48%). At the detailed industry level, financial services, business services, healthcare, general manufacturing, and technology collectively represent approximately 41% of borrowers and 47% of observations.

Table 5: Distribution of Borrowers by Industry Group

	Borrower Level (Unique)			Tranche–Lender–Borrower Level		
	Count	(%)	Cum. (%)	Count	(%)	Cum. (%)
Panel A: Broad Industry Group						
Corporates	756	82.80	82.80	15,403	77.68	77.68
Non-Bank Financials	88	9.64	92.44	2,530	12.76	90.44
Utilities	49	5.37	97.81	1,087	5.48	95.92
Other	22	2.41	100.00	810	4.08	100.00
Total	**913**	**100**		**19,830**	**100**	
Panel B: Major Industry Group						
Financial Services	89	9.75	9.75	2,536	12.79	12.79
Business Services	64	7.01	16.76	1,900	9.58	22.37
Healthcare	88	9.64	26.40	1,572	7.93	30.30
General Manufacturing	67	7.34	33.74	1,698	8.56	38.86
Technology	62	6.79	40.53	1,550	7.82	46.68
Services	50	5.48	46.01	717	3.62	50.30
Wholesale	38	4.16	50.17	854	4.31	54.61
Construction	29	3.18	53.35	526	2.65	57.26
Chemicals, Plastics & Rubber	25	2.74	56.09	577	2.91	60.17
Utilities	49	5.37	61.46	1,087	5.48	65.65
REITs	46	5.04	66.50	1,067	5.38	71.03
Real Estate	71	7.78	74.28	498	2.51	73.54
Retail & Supermarkets	32	3.50	77.78	566	2.85	76.39
Leisure and Entertainment	21	2.30	80.08	558	2.81	79.20
Other Industries	184	20.15	100.00	4,117	20.80	100.00
Total	**913**	**100**		**19,830**	**100**	

Notes: Panel A groups borrowers into broad categories ("Other" includes Media/Communications, Government, and Banks). Panel B reports detailed industry groups; "Other Industries" aggregates Agriculture, Automotive, Broadcasting, Mining, Oil & Gas, Paper & Packaging, Telecommunications, Transportation, and residual categories.

2.2.5 Pre- versus Post-Harvey Loan Conditions

Table 6 compares mean loan characteristics before and after Harvey across exposure quartiles. Two patterns stand out. First, high-exposure borrowers (Q4) experience a substantially larger spread increase: +47.51 basis points versus +26.53 in Q1. Second, quantity and maturity adjustments diverge: Q4 tranche amounts decline by $257.57 million and maturities shorten by 13.38 months, while Q1 amounts *increase* by $377.48 million with maturities essentially unchanged. These raw differences are consistent with a credit supply contraction for high-exposure borrowers and motivate the formal difference-in-differences analysis in Section 3.

Table 6: Mean Loan Characteristics: Pre vs. Post Hurricane Harvey

Variable	Pre-Harvey Mean	Post-Harvey Mean	Difference (Δ)
Q1 (Low Exposure - Control)			
Tranche Amount ($M)	387.36	764.84	+377.48
Margin (bps)	300.04	326.57	+26.53
Maturity (Months)	70.53	70.84	+0.31
Number of Lenders	7.53	8.03	+0.50
Observations	1,755	1,112	
Q4 (High Exposure - Treatment)			
Tranche Amount ($M)	739.24	481.67	-257.57
Margin (bps)	263.57	311.08	+47.51
Maturity (Months)	84.99	71.61	-13.38
Number of Lenders	8.66	8.30	-0.36
Observations	2,236	1,313	

Notes: "Pre-Harvey" includes loans issued up to 3 months before and including August 2017. "Post-Harvey" covers 1 to 3 months after the event. The sample excludes FEMA-designated counties. Differences are simple changes in means.

Table 11 in the appendix reports full summary statistics by exposure quartile. Q4 borrowers have a mean spread of 281.15 bps (versus 310.33 in Q1), longer maturities (80.03 versus 70.65 months), larger tranches ($643.95M versus $533.77M), and comparable syndicate size (8.53 versus 7.72 lenders).

2.3 Bank Geographic Exposure

We construct bank-level hurricane exposure using the FDIC Summary of Deposits (SOD), which reports branch-level deposits for all insured depository institutions as of June 30 each year.[6] We compute each bank's exposure as a deposit-weighted average of county-level hurricane damage from SHELDUS, capturing the extent to which a bank's funding base is concentrated in disaster-prone areas.

Table 7 documents substantial heterogeneity in geographic scope: approximately 42% of lenders operate in five or fewer counties, while 17.43% maintain deposits in more than 50 counties. This variation generates cross-sectional differences in exposure to localized climate shocks through banks' geographically distributed funding bases and is central to our lender-perspective identification.

Table 7: Distribution of Lenders by Geographic Presence

Number of Counties	Number of Lenders	Percent (%)	Cumulative (%)
1 county	24	9.96	9.96
2–5 counties	77	31.95	41.91
6–20 counties	61	25.31	67.22
21–50 counties	37	15.35	82.57
50+ counties	42	17.43	100.00
Total	**241**	**100.00**	

Notes: Distribution based on 2017 SOD data. A lender is present in a county if it holds a positive deposit share.

3 Empirical Strategy

We describe our empirical strategy to estimate how financial intermediaries adjust credit terms in response to large and salient physical climate shocks in areas that are hurricane risky but were not directly affected by Harvey. The unit of observation is a loan tranche extended by lender b to a borrower i located in county c at time t, measured at a monthly frequency. We focus on four primary loan outcomes: the loan spread over the benchmark

[6] Deposits are assigned to branch offices according to each bank's internal record-keeping, which may reflect account holder location, most active branch, or account origination branch.

rate (measured in basis points), tranche maturity, the number of lenders participating in the syndicate, and the logarithm of the tranche amount.

We first develop the empirical strategy from the borrower perspective, and then turn to the lender perspective to study how intermediary balance sheets shape the transmission of shocks.

3.1 Borrower Perspective

Measuring Hurricane Exposure. We construct a county-level measure of *ex ante* hurricane risk using the SHELDUS database, which reports event counts and inflation-adjusted damages (in 2022 dollars) at the county–month level. Exposure is determined by the historical vulnerability of the county in which the firm is headquartered, capturing long-run physical climate risk rather than contemporaneous damage from any single event.

For each county c and month t, let $\text{PropDmg}_{c,t}$ denote inflation-adjusted property damage. We compute a rolling-average exposure over a ten-year window (120 months) ending immediately before the current month:

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

We also construct alternative measures using total damages, per-capita damages, event counts, and average damage per event over the same window; per capita damages are used in robustness checks. For a hurricane occurring in month t_0, we collapse the series into a single pre-event index by averaging the twelve months immediately preceding the event:

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

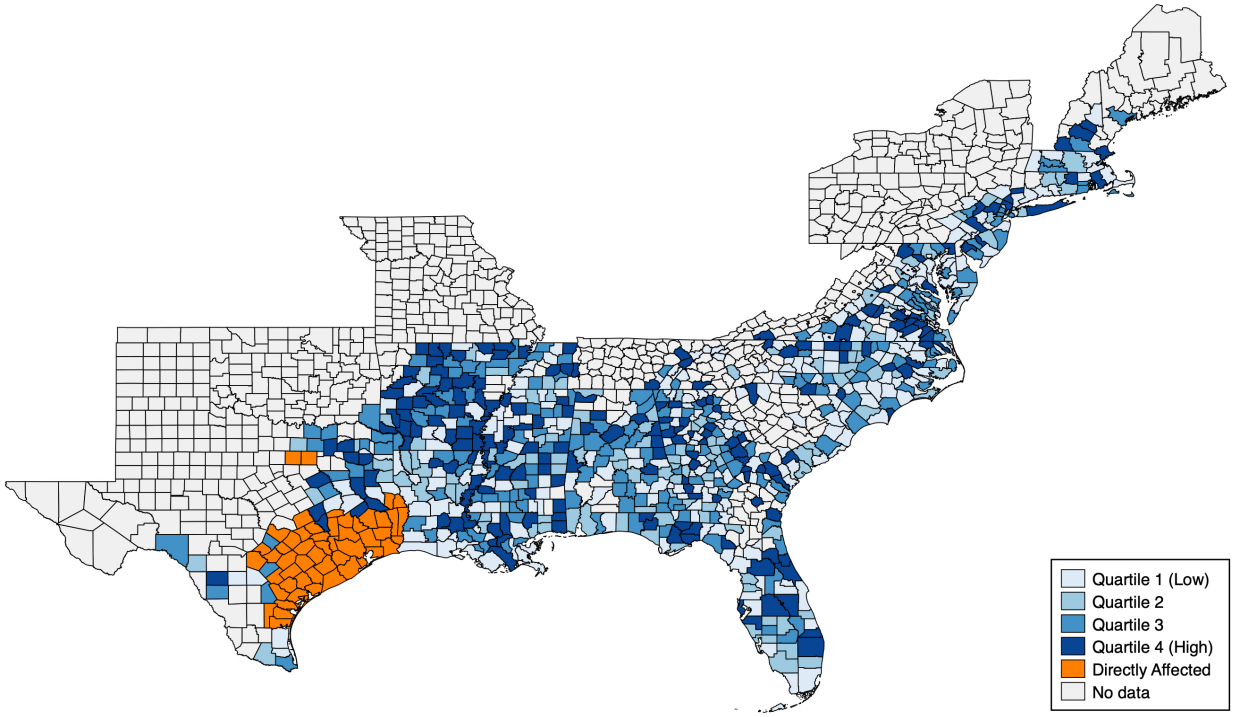
Borrower-level exposure is assigned by mapping each loan to the borrower's county $c(i)$ using ZIP code–county crosswalks, so $E_i \equiv \text{Exposure}_{c(i)}^{\text{Loc}}$.

Treatment Assignment and Sample Construction. We exclude all counties that received a FEMA disaster declaration for Hurricane Harvey, so identification relies entirely on borrowers in non-affected counties that differ in historical hurricane vulnerability. We

further drop counties with no hurricane record, which differ systematically from hurricane-prone areas and do not provide a plausible control group. Within the resulting sample, we partition counties into quartiles based on E_c: Q4 (highest exposure) forms the treated group and Q1 the control group.

Figure 2 illustrates the spatial structure. Each loan tranche inherits its borrower's county classification; we write y_{bict} for the outcome of a tranche extended by lender b to borrower i in county c at time t.

Figure 2: Hurricane Harvey Exposure and Directly Affected Counties



Notes: Orange-shaded regions are FEMA-declared counties, excluded from the sample. Blue-shaded regions are partitioned into four exposure quartiles based on $\text{Exposure}_c^{\text{Loc}}$. White counties have no data or are excluded.

Estimation. Let T denote August 2017 (Harvey's landfall). Loans originated during T are classified as pre-period, since Harvey struck late in August and most terms were negotiated before landfall. We estimate:

$$y_{bict} = \beta \left(\text{HighExp}_{c(i)} \times \text{Post}_t\right) + \alpha_b + \alpha_{c(i)} + \alpha_t + \alpha_{\text{ind}} + \alpha_{\text{ltype}} + \alpha_{\text{mktseg}} + \alpha_{\text{pp}} + \varepsilon_{bict}, \quad (1)$$

where $\text{Post}_t = \mathbb{1}\{t > T\}$. County fixed effects ($\alpha_{c(i)}$) absorb time-invariant location characteristics including geography and baseline disaster risk. Lender fixed effects (α_b) absorb persistent differences in pricing policies and balance-sheet structure, so identification exploits *within-lender, cross-location variation*: β captures how the *same* lender adjusts terms across counties with different exposure histories after Harvey. Time fixed effects (α_t) absorb aggregate credit conditions; industry (α_{ind}), loan type (α_{ltype}), market segment (α_{mktseg}), and performance pricing (α_{pp}) fixed effects control for sectoral demand, facility structure, and covenant-linked pricing. Standard errors are clustered at the lender level.

To trace dynamics and test parallel trends, we estimate:

$$y_{bict} = \sum_{\substack{\tau=-3 \\ \tau\neq 0}}^{+3} \beta_\tau \left(\mathbb{1}\{t - T = \tau\} \times \text{HighExp}_{c(i)} \right) + \alpha_b + \alpha_{c(i)} + \alpha_t + \mathbf{X}'\gamma + \varepsilon_{bict}, \tag{2}$$

where $\mathbf{X}$ collects industry, loan type, market segment, and performance pricing fixed effects, and the landfall month ($\tau = 0$) is the omitted reference period. Insignificant pre-period coefficients $\{\beta_{-3}, \beta_{-2}, \beta_{-1}\}$ support parallel trends. Because all directly affected counties are excluded, the post-period coefficients reflect changes in *perceived* hurricane risk rather than realized damage.

The coefficient β captures equilibrium credit conditions. A credit supply interpretation requires *no differential demand shift*, such that, conditional on fixed effects, credit demand does not vary differentially across exposure quartiles at the time of Harvey. This condition is plausible for two reasons. First, the treated borrowers experienced no direct impact from Harvey, which means no physical damage, no FEMA declarations, no change in local economic conditions, so there is no obvious mechanism for a differential demand shift at the precise month of landfall. Second, the remaining demand-side threat would require firms in historically hurricane-prone but currently unaffected counties to preemptively adjust borrowing in response to a distant hurricane, an arguably implausible behavioral response. The pattern of results offers a further diagnostic: a supply contraction predicts simultaneous tightening across all margins (higher spreads, smaller amounts, shorter maturities, fewer lenders), while a demand shift would typically move price and quantity in offsetting directions. As shown in Section 4, we observe the former.

Identifying assumptions. β is causally identified under four conditions: *(i) parallel trends*—absent Harvey, loan outcomes in high- and low-exposure counties would have evolved identically, conditional on fixed effects; *(ii) no anticipation*—lenders did not reprice hurricane risk before landfall; *(iii) no spillovers*—Harvey did not shift spreads in control counties through a market-wide reassessment (if present, this attenuates β toward zero); and *(iv) exogeneity of exposure classification*—the quartile assignment correctly captures lenders' perceptions of hurricane vulnerability (measurement error again attenuates β). We assess (i) and (ii) through event-study pre-trends.

3.2 Lender Perspective

We now exploit cross-lender variation in hurricane exposure to study how climate risk propagates through intermediary balance sheets. Even when lending to borrowers in unaffected counties, lenders may adjust credit terms if the hurricane impairs their financial condition or triggers a reassessment of latent portfolio risk. We construct two complementary exposure measures to disentangle these channels.

3.2.1 Lender Exposure Measures

Specification I: Portfolio exposure to non-Harvey hurricane-prone counties. This measure captures a lender's portfolio concentration in historically hurricane-prone counties that were *not* directly affected by Harvey:

$$\text{ExpoDeposit}_b = \sum_{c \notin \mathcal{H}} \text{DepositShare}_{b,c} \times \text{HurrRisk}_c, \tag{3}$$

where HurrRisk_c is the percentile rank of county c's average hurricane property damage over the preceding 120-month window, computed from SHELDUS. An analogous loan-based measure is defined symmetrically. Because the summation excludes all Harvey-declared counties, this measure captures no direct losses from the storm. It instead identifies a *belief-updating channel*: Harvey may cause lenders with concentrated positions in hurricane-vulnerable regions to reassess latent portfolio risk and tighten credit preemptively, even absent realized losses.

Specification II: Direct exposure to Harvey-affected counties. For each lender parent b, we compute the share of deposits held in counties that received a FEMA disaster declaration for Harvey:

$$\text{LenderExp}_b^D = \sum_{c \in \mathcal{H}} \text{DepositShare}_{b,c,\,2017}, \tag{4}$$

where $\mathcal{H}$ denotes Harvey-affected counties and $\text{DepositShare}_{b,c,\,2017}$ is measured from the FDIC Summary of Deposits as of June 2017, prior to landfall. An analogous loan-based measure replaces deposit shares with the lender's share of outstanding syndicated loan volume in $\mathcal{H}$. These measures capture the lender's direct financial stake in the disaster zone—deposit withdrawals, loan impairments, increased provisioning—and identify a *balance-sheet channel*: stressed lenders may tighten credit to all borrowers, regardless of borrower-specific hurricane risk.

Treatment assignment. Under both specifications, we partition lenders into quartiles and compare Q4 (highest exposure) to Q1 (lowest). See Figures 9 and 8 for the geographic distribution of lender treatment groups.

3.2.2 Estimation

For each borrower-location subsample $S \in \{\text{risky}, \text{safe}\}$, we estimate:

$$y_{bit} = \beta^S \left(\text{HighExpoLender}_b \times \text{Post}_t\right) + \alpha_b + \alpha_i + \alpha_t + \alpha_{\text{ind}} + \alpha_{\text{ltype}} + \alpha_{\text{mktseg}} + \alpha_{\text{pp}} + \varepsilon_{bit}, \tag{5}$$

where y_{bit} is a loan outcome for a tranche extended by lender b to borrower i at time t, and HighExpoLender_b is defined using either Specification I or II.

The key difference from the borrower perspective is the fixed-effect structure. Here we include *borrower* fixed effects (α_i) rather than county fixed effects, absorbing all time-invariant firm characteristics, such as location, credit quality, industry, business model. Identification therefore comes from *within-borrower, across-lender variation over time*: for the same firm, how do the terms of tranches involving lenders with different exposure profiles differ after Harvey?

An institutional feature of syndicated lending bears on interpretation. Within a tranche,

all participants face identical contract terms set by the lead arranger. The within-borrower variation therefore operates across *different tranches* to the same firm, where those tranches involve syndicates with different exposure compositions. If exposed lenders become more reluctant to participate, the lead arranger must adjust terms to clear the market, so tighter terms on tranches involving high-exposure lenders reflect supply-side pressure.

We split the sample by borrower location; risky counties (historical hurricane exposure) versus safe counties (no hurricane history) to test whether lenders adjust differentially depending on the borrower's climate risk profile. This decomposition is central to distinguishing the balance-sheet channel from belief updating, as discussed below.

To assess parallel trends, we estimate the event-study analogue:

$$y_{bit} = \sum_{\substack{\tau=-3 \\ \tau\neq -1}}^{+3} \beta_\tau^S \left(\mathbb{1}\{t - T = \tau\} \times \text{ExpoLender}_b\right) + \alpha_b + \alpha_i + \alpha_t + \mathbf{X}'\gamma + \varepsilon_{bit}, \tag{6}$$

where $\mathbf{X}$ collects industry, loan type, market segment, and performance pricing fixed effects. Standard errors are clustered at the lender parent level throughout.

The coefficient β^S captures equilibrium loan terms. A credit supply interpretation requires two conditions: *(i)* the same borrower does not condition its credit demand on the hurricane exposure of the lender's portfolio, which is plausible since borrowers are price-takers with respect to syndicate composition; and *(ii)* the matching of borrowers to high- versus low-exposure lenders does not shift endogenously after Harvey in ways correlated with demand. Borrower fixed effects absorb the permanent match component, and the event-study pre-trends provide an indirect test against time-varying sorting.

3.2.3 Distinguishing Channels

The two specifications, combined with the risky/safe decomposition, generate a 2×2 matrix of coefficients that disciplines the interpretation.

Belief-updating channel (Specification I). If Harvey causes lenders to reassess latent hurricane risk in their broader portfolio, the effect should be concentrated among borrowers in risky locations, where the updated risk assessment is directly relevant, and manifest primarily under Specification I, where the exposure measure is orthogonal to direct Harvey

losses. The predicted pattern is $\beta_{\text{II}}^{\text{risky}} > 0$ with $\beta_{\text{II}}^{\text{safe}} \leq 0$, the latter reflecting portfolio rebalancing toward safer areas. If Specification II also shows effects only in risky locations ($\beta_{\text{I}}^{\text{risky}} > 0$, $\beta_{\text{I}}^{\text{safe}} \approx 0$), it suggests that even directly affected lenders are selectively repricing hurricane-exposed credit rather than uniformly passing through balance-sheet stress.

Balance-sheet channel (Specification II). If Harvey impairs the financial condition of directly exposed lenders, they may tighten credit to *all* borrowers, irrespective of borrower-specific hurricane risk, because their capacity to bear risk has declined. This predicts $\beta_{\text{I}}^{\text{risky}} > 0$ *and* $\beta_{\text{I}}^{\text{safe}} > 0$, with similar magnitudes. Specification I should produce weaker effects under this channel, since lenders with portfolios in non-Harvey hurricane-prone counties suffered no direct losses.

3.2.4 Identifying Assumptions

β^S is causally identified under four conditions: *(i) parallel trends*—absent Harvey, loan terms for the same borrower would have evolved identically across lenders with different exposure profiles; *(ii) no anticipation*—lenders did not adjust syndicated lending before Harvey's landfall; *(iii) no spillovers*—low-exposure lenders were not indirectly affected through general equilibrium channels (if present, this attenuates β^S toward zero); and *(iv) exogeneity of portfolio exposure*—the pre-Harvey geographic distribution of each lender's deposits and loans is uncorrelated with lender-specific, time-varying shocks to lending behavior. We assess (i) and (ii) through event-study pre-trends.

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, which provides a sharp and salient shock to perceived physical climate risk.

We first study credit conditions from the borrower perspective following Harvey. 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 credit supply adjustment, exploring bank and nonbanks lenders behavior.

4.1 Harvey Hurricane: Borrower's Perspective

From the borrower's perspective, treatment is assigned based on the historical hurricane exposure of the borrower's county, excluding all FEMA-declared counties that experienced direct damage from Harvey. Because treated borrowers are located in counties that were not directly hit by the hurricane and differ from control borrowers only in their long-run vulnerability to hurricane risk, the estimates isolate changes in how lenders price perceived climate risk rather than responses to realized local damage.[7] We first present estimates for all borrowers and then examine heterogeneity between financial and non-financial borrowers, which speaks directly to the channels through which climate risk is transmitted in credit markets.

Table 8 reports the baseline difference-in-differences estimates for all borrowers following Hurricane Harvey. Borrowers located in high-exposure counties (Q4) face significantly tighter credit conditions relative to those in low-exposure counties (Q1) in the aftermath of the hurricane. The DiD estimate on loan spreads is approximately 66 basis points, representing the differential increase for high-exposure borrowers over and above any aggregate post-Harvey change in credit conditions, and corresponding to roughly a 25 percent increase relative to the pre-Harvey mean spread of 263 basis points in the treatment group. Syndicate size falls by nearly two lenders, tranche amounts decline by approximately 28 percent (0.333 log points), and maturities shorten by about 3.3 months, or roughly 4 percent relative to the pre-Harvey mean of 85 months for high-exposure borrowers. The simultaneous tightening across all four margins, price, quantity, syndicate participation, and tenor, is consistent with a contraction in credit supply rather than a demand-side shift. As a robustness check, we re-estimate the baseline specification using county-level hurricane exposure measured by historical property damage per capita. Appendix Table 15 shows that the results are very similar to the baseline estimates.

[7] There is no obvious demand-side explanation for the results. Firms headquartered in historically hurricane-prone counties that experienced no direct shock from Harvey faced no damage, no operational disruption, and no change in local economic conditions at the time of landfall. It is therefore difficult to construct a mechanism by which these firms would differentially alter their credit demand at the precise month of the event.

Table 8: Hurricane Harvey Impact on Loan Terms: All Borrowers

	(1) Margin	(2) No. Lenders	(3) Ln Amount	(4) Maturity
DID	65.972***	-1.918***	-0.333***	-3.307**
	(16.28)	(0.53)	(0.13)	(1.81)
Observations	6,320	6,320	6,320	6,300
R^2	0.612	0.657	0.605	0.465
County FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

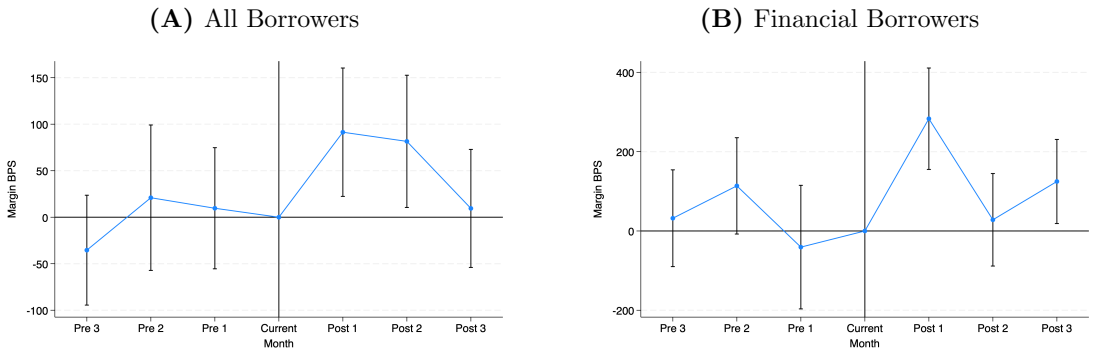
Notes: This table reports Difference-in-Differences estimates for Hurricane Harvey using borrower exposure based on total property damage, comparing high-exposure counties (Q4) to the control group (Q1). Standard errors are clustered at the lender level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 presents the event-study dynamics. Panel (A) shows the estimated coefficients for all borrowers in the three months before and after Harvey's landfall. Pre-period coefficients are small and statistically indistinguishable from zero, supporting the parallel trends assumption: high- and low-exposure counties were on similar trajectories prior to the hurricane. The spread differential rises sharply at the month of landfall and then gradually reverts toward baseline over the following months, coinciding with the end of the hurricane season when the near-term probability of additional storm strikes diminishes. This seasonal pattern is consistent with lenders conditioning on the near-term probability of a second major landfall during the active Atlantic hurricane season (June–November), which drops sharply once the season closes. It is inconsistent with a permanent upward revision to the long-run climate risk of these locations, which would predict a persistent and non-reverting spread differential.

The syndicated loan results capture credit conditions for large corporate borrowers. To assess whether similar repricing dynamics extend to small businesses, which face fundamentally different financing constraints and rely more on relationship-based lending than on syndicated markets, we examine interest rates on SBA 7(a) loans around Hurricane Harvey. Figure 10 presents event-study estimates of these interest rates. Consistent with the syndicated loan analysis, pre-event coefficients are small and statistically indistinguishable from zero, supporting the parallel trends assumption. Following the hurricane, interest rates on SBA 7(a) loans increase, with the largest response occurring one month after the event.

Although the estimates are less precise, 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 findings suggest that hurricane-induced increases in perceived climate risk propagate across financing segments and affect both large corporate borrowers and small businesses.

Figure 3: Harvey Impact on Syndicated Loan Spread



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). 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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.

The heterogeneity across borrower types provides direct evidence on the transmission mechanism: climate risk propagates primarily through intermediary balance sheets and lending networks, not through a broad deterioration in borrower fundamentals. For financial borrowers (see table 12 in the appendix), the difference-in-differences coefficient on loan spreads reaches approximately 110 basis points, nearly twice the aggregate estimate, and is accompanied by sharp contractions along all non-price margins: syndicate size falls by roughly five lenders, tranche amounts decline by 46 log points, and maturities shorten by almost 12 months. All four estimates are statistically significant at the 1% level. Panel (B) of Figure 3 confirms that these effects emerge immediately at landfall, with flat pre-trends providing no evidence of differential anticipatory behavior prior to the event.

By contrast, non-financial borrowers (see table 13 in the appendix) exhibit no statistically significant increase in loan spreads following Harvey. The spread coefficient is approximately 10 basis points and is insignificant. Syndicate participation actually increases

for non-financial firms, while amounts and maturities are largely unchanged. This pattern stands in sharp contrast to the systematic tightening observed for financial borrowers and argues against a broad deterioration in borrower fundamentals as the primary driver of the aggregate results.

The concentration of effects among financial borrowers suggests that climate risk is transmitted through intermediary networks and lending relationships rather than through a generalized repricing of borrower creditworthiness. Financial firms, which are more deeply embedded in the financial system and more reliant on intermediary-provided credit, bear a disproportionate share of the repricing following a salient climate shock. Non-financial firms, whose credit demand is less sensitive to intermediary stress and whose local economic conditions are unaffected by the hurricane, are largely insulated. What the dynamics do establish clearly is that the repricing is transitory and tied to the window of active hurricane risk, which suggests lenders are updating their assessment of near-term conditional risk rather than revising their views about the long-run climate exposure of these locations.

This heterogeneity across borrower types, together with the transitory nature of the pricing response, motivates the lender-perspective analysis in the following section, which directly traces how hurricane exposure on intermediary balance sheets shapes credit supply decisions.

4.2 Harvey Hurricane: Lender Perspective

We now turn to the lender perspective to examine how hurricane risk propagates through financial intermediaries' balance sheets. The borrower-side results showed that credit tightening is concentrated among financial firms, pointing to intermediary channels rather than changes in borrower fundamentals. We therefore trace this mechanism directly by exploiting cross-lender variation in pre-Harvey exposure to hurricane risk. Specifically, we consider both exposure to non-Harvey hurricane-prone counties and direct exposure to Harvey-affected areas, using two complementary measures: lenders' deposit footprints, which capture funding-side vulnerability, and their existing syndicated loan portfolios, which capture asset-side risk. For each channel, we analyze lending to borrowers in risky and safe locations separately. This distinction allows us to differentiate between two mechanisms: a belief-updating channel, in which Harvey leads lenders to reassess latent risks concentrated in hurricane-prone regions,

and a balance-sheet channel, in which directly exposed lenders tighten credit uniformly across all borrowers, regardless of location. Finally, we decompose the results by intermediary type, showing that banks and nonbanks adjust their lending behavior in fundamentally different ways.

Deposit-side exposure to non-Harvey hurricane-prone counties. Table 9 examines how lenders' pre-Harvey exposure to hurricane risk through their deposit footprint shapes credit supply in the aftermath of the hurricane. Two findings stand out. First, in risky locations, lenders with greater deposit exposure to hurricane-prone counties participate in tranches with significantly higher spreads relative to less exposed lenders, with the difference-in-differences coefficient reaching 0.34 basis points per unit of deposit exposure. Loan amounts and maturities show no economically meaningful adjustment, indicating that the funding-side channel operates primarily through repricing rather than quantity rationing in risky areas. Second, in safe locations, the pattern reverses sharply along the price margin: more exposed lenders participate in tranches with lower spreads (coefficient of -0.22 basis points), and loan amounts are modestly larger. This sign reversal is the signature of active portfolio rebalancing, which means the same lenders who tighten terms in exposed regions simultaneously offer more favorable conditions in unexposed ones, consistent with geographic risk reallocation rather than a uniform balance-sheet contraction.

Two aspects of this pattern speak directly to channel identification. The exposure measure in Specification I excludes all Harvey-affected counties by construction, so these lenders suffered no direct losses from the storm. The effects therefore cannot reflect balance-sheet impairment. Instead, Harvey appears to function as a signal that prompts lenders with concentrated funding bases in hurricane-vulnerable regions to reassess the latent risk embedded in their portfolios and reprice accordingly, a belief-updating channel. Moreover, the asymmetry across risky and safe locations, tightening in one, easing in the other, is precisely what portfolio rebalancing predicts and what a uniform balance-sheet channel would not.

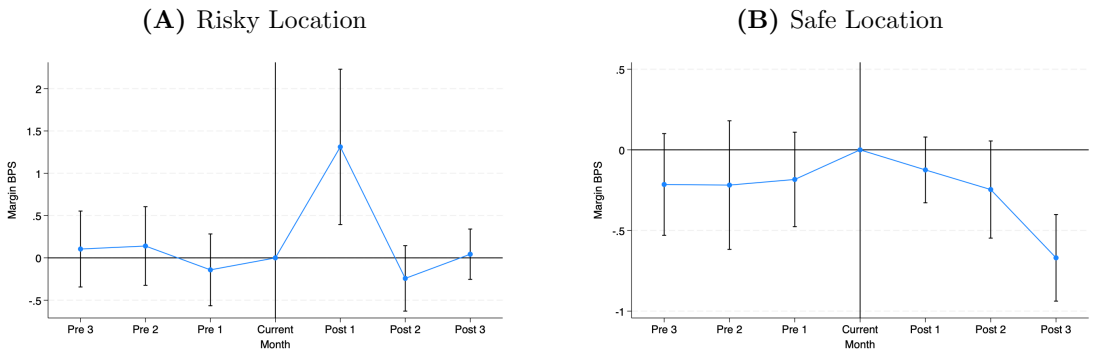
Table 9: Hurricane Impact in Syndicated Loan Spread through Deposit Channel

	Risky Location			**Safe Location**		
	(1) Margin BPS	(2) Ln Amount	(3) Maturity	(4) Margin BPS	(5) Ln Amount	(6) Maturity
DID	0.340***	0.001**	-0.038***	-0.216***	0.001***	-0.003
	(0.11)	(0.00)	(0.01)	(0.06)	(0.00)	(0.01)
Observations	2,863	2,863	2,863	10,825	10,825	10,825
R^2	0.784	0.807	0.728	0.793	0.759	0.654
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports Difference-in-Differences results for Hurricane Harvey from the lender perspective using deposit-based exposure to pre-Harvey 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 the corresponding event-study estimates and confirms that the spread differential in risky locations emerges sharply at the time of Harvey's landfall, with flat pre-period coefficients supporting the parallel trends assumption. The timing is informative: the repricing appears immediately at landfall and does not build gradually beforehand, ruling out anticipatory behavior and consistent with Harvey functioning as a discrete updating event rather than the culmination of a pre-existing trend.

Figure 4: Hurricane Impact in Syndicated Loan Spread through Deposit Channel



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey from the lender perspective using pre-Harvey hurricane exposure through the deposit channel. 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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.

Asset-side exposure to non-Harvey hurricane-prone counties. Table 10 reports analogous results using loan-portfolio exposure rather than deposit-based exposure, capturing lenders' asset-side vulnerability to hurricane risk. The results are broadly consistent with the deposit channel but with one important difference. In risky locations, lenders with greater loan-portfolio concentration in hurricane-prone counties charge significantly higher spreads and extend smaller loan amounts following Harvey, the spread coefficient reaches approximately 12.5 basis points and the amount coefficient implies a contraction of roughly 4 percent (0.042 log points). In safe locations, however, estimated coefficients are small and statistically indistinguishable from zero across all three outcome margins.

This contrast between channels is informative. The deposit channel shows a clear reallocation pattern: lenders tighten credit in risky areas and expand it in safer ones. In contrast, the asset channel leads to tightening in risky areas without a corresponding expansion elsewhere. This difference suggests that funding-side exposure creates a stronger incentive for geographic reallocation. When deposits are concentrated in hurricane-prone regions, a lender's liabilities are directly linked to local economic conditions, increasing the need to rebalance toward safer areas. By contrast, asset-side exposure affects only the risk of the existing loan portfolio, leading primarily to more targeted repricing rather than a broader shift of credit across locations.

Taken together, the deposit and asset channel results are consistent with belief-updating as the dominant mechanism. In both specifications, effects are concentrated in risky locations, which is precisely where an updated assessment of hurricane vulnerability would be most relevant. Neither channel produces the pattern, tightening uniformly across risky and safe locations, that a pure balance-sheet impairment channel would predict.

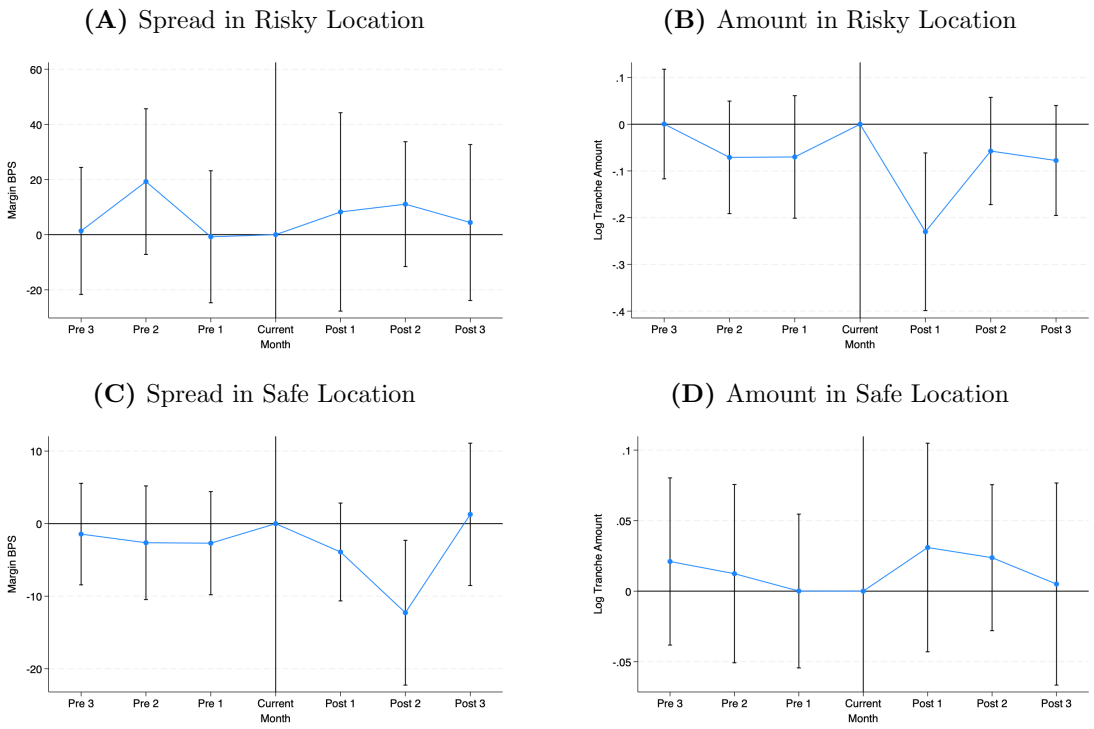
Table 10: Hurricane Impact in Syndicated Loan Spread through Asset Channel

	Risky Location			**Safe Location**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Margin BPS	Ln Amount	Maturity	Margin BPS	Ln Amount	Maturity
DID	12.536**	-0.042**	-0.541	-4.595	0.007	-0.547
	(5.82)	(0.02)	(1.11)	(3.47)	(0.03)	(0.65)
Observations	2294	2294	2294	8963	8963	8963
R^2	0.759	0.791	0.723	0.765	0.749	0.643
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

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 presents the event-study dynamics and confirms that both the spread increase and quantity contraction in risky locations emerge sharply at landfall with no evidence of pre-trends. The safe-location estimates remain flat throughout the event window, reinforcing the conclusion that asset-side exposure generates a targeted rather than indiscriminate adjustment.

Figure 5: Hurricane Impact in Syndicated Loan Spread and Amount through Asset Channel



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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.

Bank and nonbank lenders: asymmetric roles in risk transmission. Figure 6 decomposes the asset-channel results by lender type and reveals a striking divergence that is central to the paper's contribution. Among bank lenders, exposed institutions reduce loan amounts in risky locations following Harvey while modestly increasing amounts in safe locations, a pattern consistent with active portfolio rebalancing away from climate-vulnerable regions and toward safer ones. This is precisely the behavior one would expect from regulated intermediaries facing capital constraints, heightened supervisory scrutiny of concentrated geographic exposures, and internal risk limits that treat hurricane-prone portfolios as elevated risk following a salient shock.

Figure 6: Banks and Nonbank Sub-Sample: Loan Amount (Asset Channel)



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey. The outcome variable is the syndicated loan amount at the tranche level. The sample is split by lender type: bank lenders (top row) and nonbank lenders (bottom row). 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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.

Nonbank lenders display the opposite pattern in risky locations: exposed nonbanks expand loan amounts following the hurricane, stepping into the gap left by retreating banks and absorbing climate risk that regulated intermediaries are shedding. In safe locations, nonbanks exhibit no systematic response. This asymmetry, banks contracting in risky areas while nonbanks expand, implies that climate risk is not eliminated from the financial system but rather redistributed across intermediary types, with the marginal lender in hurricane-exposed regions increasingly being a nonbank institution operating outside the traditional prudential perimeter.

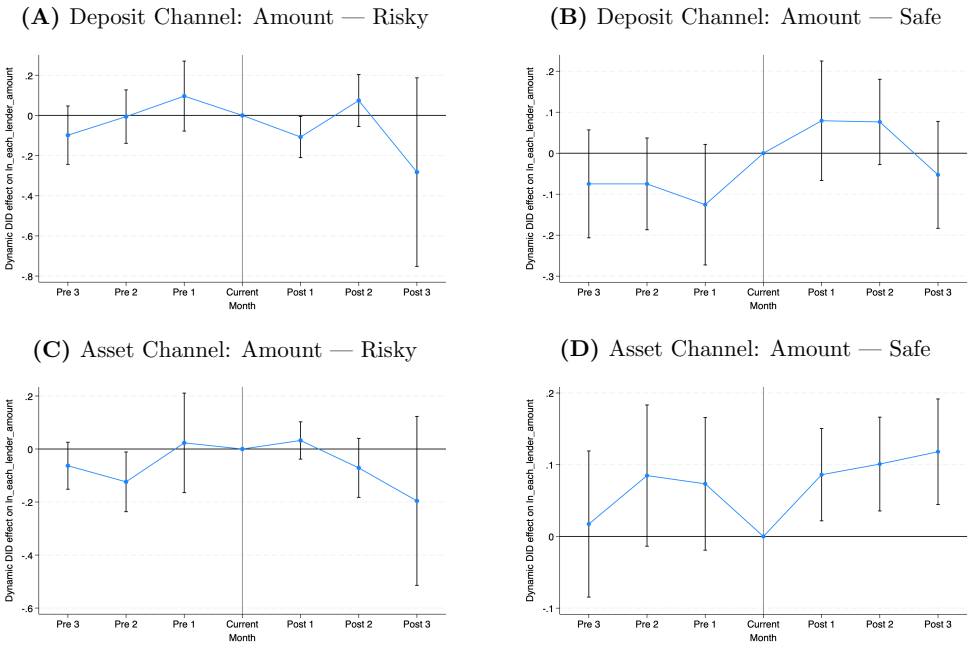
Critically, the nonbank expansion along quantity margins in risky locations is not accompanied by favorable pricing: from the borrower perspective, aggregate credit conditions in hurricane-prone areas remain tighter after Harvey even as nonbanks increase their sup-

ply. This suggests that nonbanks partially stabilize credit availability but do not fully offset the tightening initiated by banks, and do so at terms that still reflect elevated perceived risk. The net effect is a reallocation of climate risk toward less regulated intermediaries, a shift that may reduce short-run credit disruption but raises longer-run questions about the concentration of correlated climate losses in segments of the financial system subject to less oversight.

Direct exposure to Harvey-affected counties. The results above use exposure to non-Harvey hurricane-prone counties, isolating the belief-updating channel by construction. We now turn to lenders with direct deposit and loan exposure to Harvey-affected counties, which additionally captures balance-sheet impairment. This comparison allows us to assess whether the transmission mechanism changes when lenders face realized rather than merely reassessed losses.

Figures 7 and 11 (in the appendix) present the dynamic results for bank lenders through the deposit and asset channels separately. Across both channels, directly exposed banks reduce loan amounts in risky locations following Harvey, replicating the pattern from the portfolio exposure analysis. Notably, the safe-location response is more muted and statistically insignificant for directly exposed banks, in contrast to the safe-location easing visible in the deposit channel under Specification I. This difference suggests that when lenders face realized balance-sheet losses, rather than merely updating beliefs, the rebalancing incentive toward safer areas is attenuated, possibly because direct impairment constrains overall lending capacity rather than simply redirecting it. The broad portfolio contraction in safe areas visible in the pooled sample is therefore not driven by directly exposed banks alone.

Figure 7: Bank Subsample: Impact on Loan Amount (Affected Deposit/Asset Channel)



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey for the bank subsample. The outcome variable is the log loan amount at the lender-tranche level. The top row uses deposit-channel exposure; the bottom row uses asset-channel exposure. 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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.

Figure 12 (appendix) examines nonbank lenders through the asset channel for direct Harvey exposure. The results should be interpreted with caution. Panel (A) shows a pre-trend in the amount outcome for risky locations, as coefficients in the pre-period are not uniformly flat. This weakens the parallel trends assumption and limits the causal interpretation of the post-event response. Panel (B) also displays pre-period movement in safe locations, further complicating clean identification for this subsample.

We therefore treat this figure as suggestive rather than causal evidence. With this caveat, the post-event pattern in Panel (A) is directionally consistent with the nonbank stabilizer role documented under Specification I. Exposed nonbanks do not appear to contract lending in risky locations following Harvey, and the point estimates, if anything, suggest an expansion. However, given the instability in pre-trends, we cannot rule out that this pattern reflects pre-existing differences between high- and low-exposure nonbank lenders rather than a response to the hurricane. The bank–nonbank asymmetry emphasized in the paper therefore relies

primarily on the portfolio exposure results in Figure 6, where parallel trends hold more convincingly. The direct-exposure results for nonbanks should be viewed as supplementary and directional.

Taken together, the lender-perspective results point to belief-updating as the primary transmission channel, with portfolio rebalancing — away from risky locations and toward safe ones among exposed banks — as the main behavioral response. The balance-sheet channel is present but secondary: directly exposed banks tighten credit in risky areas but do not generate the same geographic reallocation as lenders responding to updated risk beliefs. Across both channels and both exposure measures, nonbank lenders consistently absorb the credit withdrawn by banks in hurricane-exposed regions, partially stabilizing supply but redistributing climate risk toward less regulated intermediaries in the process.

5 Conclusion

This paper studies how localized physical climate shocks transmit through financial intermediaries and affect credit conditions beyond directly impacted areas. Using Hurricane Harvey and U.S. syndicated loan data, we isolate the indirect transmission of climate risk by focusing on borrowers in hurricane-prone but unaffected counties, where local economic conditions remained unchanged. This design allows us to separate the intermediary channel from the direct damage channel and addresses a central question for financial stability: not only whether climate risk is priced, but how it propagates through the financial system and who ultimately bears it.

Our first finding is that local disaster shocks increase loan prices well beyond the affected area. Syndicated loan spreads rise by approximately 66 basis points for borrowers in high-exposure but unaffected counties, roughly 25 percent above pre-event levels. At the same time, loan amounts, maturities, and syndicate participation all decline. The fact that all margins tighten simultaneously, and that these effects revert within the hurricane season window, indicates a credit supply response driven by elevated short-term perceived risk rather than a permanent reassessment of long-run climate vulnerability or a deterioration in borrower fundamentals. Our second finding is that transmission operates primarily through intermediary networks rather than borrower risk. Financial firms, which are more embedded in lending relationships and rely more heavily on intermediary-provided credit, experience

spread increases of around 110 basis points along with sharp contractions in all non-price margins. In contrast, non-financial firms are largely unaffected. This asymmetry rules out a broad repricing of borrower creditworthiness and instead points to the financial system itself as the key amplifier of local climate shocks.

Our third and most novel finding concerns the role of lender identity. Banks and nonbanks respond to the same shock in fundamentally different ways. Exposed banks tighten credit in hurricane-prone locations and reallocate lending toward safer areas, consistent with portfolio rebalancing under capital constraints and supervisory pressure. Nonbank lenders move in the opposite direction, expanding credit in risky locations precisely where banks are retreating. This partially stabilizes credit supply but shifts climate risk toward less regulated intermediaries. Importantly, this expansion is not accompanied by more favorable pricing, so overall credit conditions in exposed areas remain tighter. As a result, the marginal lender in hurricane-prone regions increasingly lies outside the traditional prudential perimeter. Our results indicate that belief updating is the dominant mechanism rather than a balance-sheet impairment channel. Lender responses are concentrated in risky locations and absent in safer ones, consistent with selective reassessment of hurricane-related risk. A balance-sheet impairment channel would arise if the hurricane weakened lenders' financial positions, for example through losses, funding pressures, or reduced capital, leading them to tighten credit across all borrowers regardless of location. We do not observe this pattern. Instead, Harvey appears to function primarily as a signal that leads lenders with concentrated exposure to reassess latent portfolio risk.

These findings have important implications. For prudential policy, the divergence between banks and nonbanks suggests that frameworks focused on regulated intermediaries may provide an incomplete view of how climate risk is distributed across the financial system. As banks reduce exposure to climate-vulnerable regions, risk may accumulate in nonbank portfolios that are less regulated and potentially more sensitive to liquidity stress. For central banks conducting climate stress tests, our results highlight that the identity of the marginal lender matters. Aggregate credit supply may appear stable even as it shifts toward intermediaries with lower loss-absorbing capacity.

Several questions remain open. First, the long-run consequences of this reallocation are not yet clear. Whether the accumulation of climate-exposed credit in nonbank portfolios increases systemic vulnerability over time remains an open empirical question, particularly

given data limitations. Second, our analysis focuses on a single, highly salient event. The prominence of Hurricane Harvey may have amplified belief updating, and it is important to assess whether similar dynamics arise following less visible climate shocks. Third, the welfare implications of bank and nonbank substitution are ambiguous. While nonbank expansion may stabilize credit in the short run, it may also concentrate risk in less regulated parts of the financial system, potentially increasing fragility during periods of stress. Understanding this trade-off is central for the design of effective climate risk regulation.

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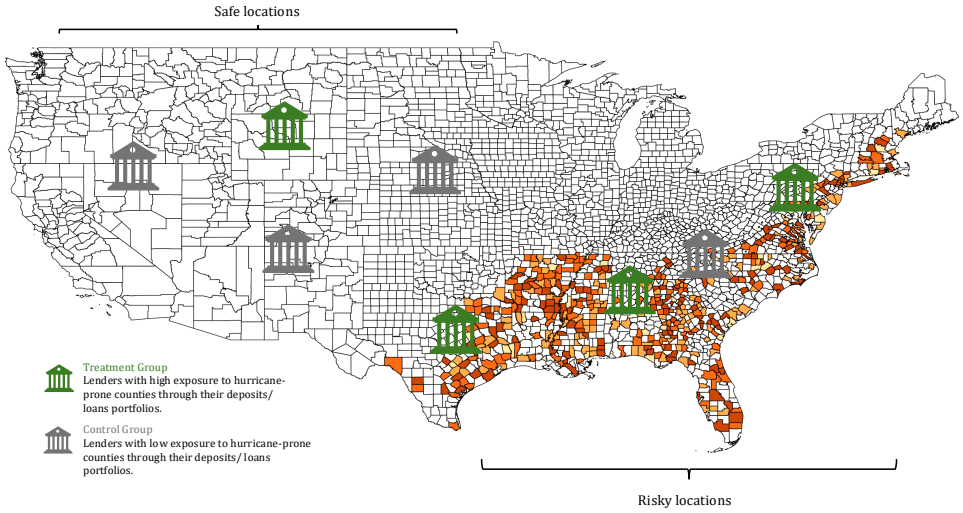
6 Appendix

Table 11: Loan Characteristics by Harvey Exposure Quartile

Variable	Mean	25th	Median	75th	Std. Dev.
Q1 (Low Exposure)					
Tranche Amount ($M)	533.77	75.00	225.00	556.95	877.61
Margin (bps)	310.33	150.00	300.00	400.00	184.46
Maturity (Months)	70.65	60.00	60.00	84.00	28.21
Number of Lenders	7.72	4.00	6.00	11.00	5.57
Observations			2,867		
Q4 (High Exposure)					
Tranche Amount ($M)	643.95	150.00	350.00	700.00	871.37
Margin (bps)	281.15	175.00	225.00	350.00	172.52
Maturity (Months)	80.03	60.00	83.00	96.00	29.13
Number of Lenders	8.53	4.00	8.00	12.00	5.42
Observations			3,549		

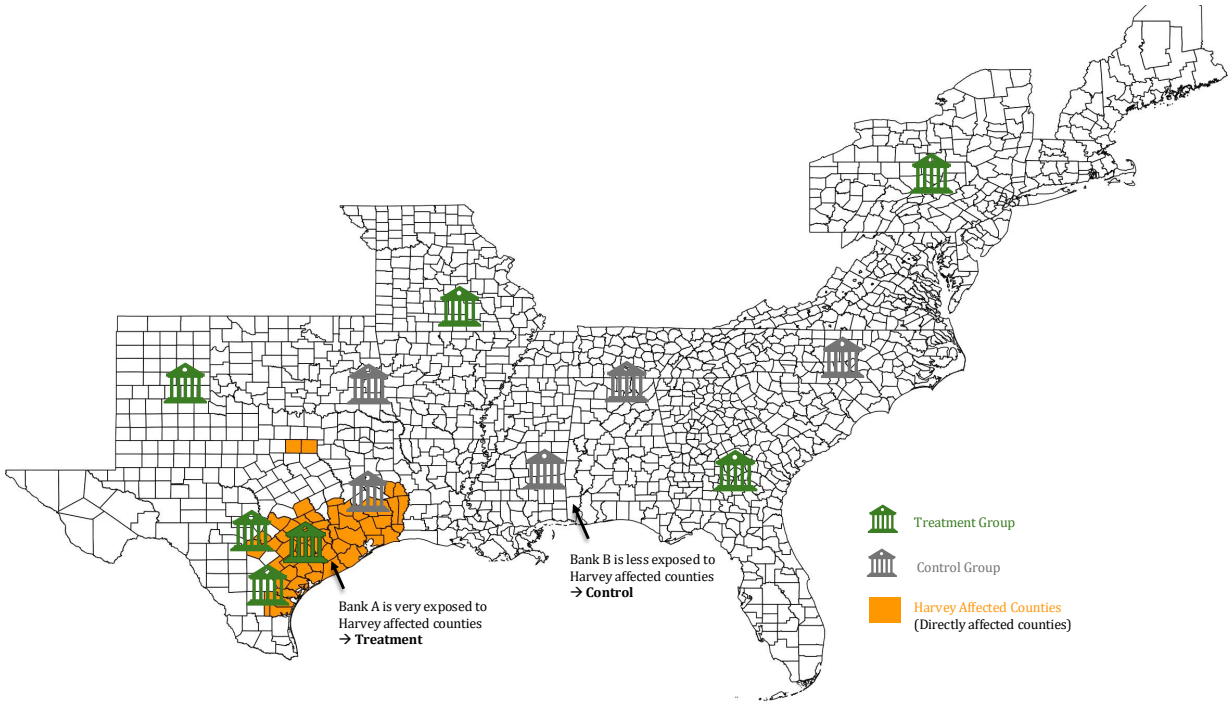
Notes: Summary statistics for syndicated loan tranches within ±3 months of Harvey. Sample restricted to hurricane-prone counties excluding directly affected areas. Q1 (Q4) is the lowest (highest) exposure quartile. Unit of observation is a tranche–lender pair.

Figure 8: Lender Treatment Groups: Pre-Harvey Hurricane Risk Exposure



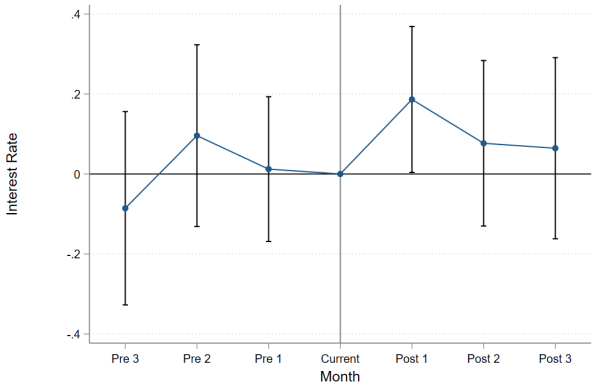
Notes: This figure is for illustrative purposes and shows the classification of lenders into treatment and control groups based on their pre-Harvey exposure to hurricane-prone counties through their loan and deposit portfolios. Lenders with higher exposure are assigned to the treatment group, while those with lower exposure form the control group. In the analysis of new loans after Harvey, safe locations refer to counties with no historical hurricane risk, while risky locations correspond to counties historically exposed to hurricanes.

Figure 9: Lender Treatment Groups: Harvey-Affected Exposure



Notes: This figure is for illustrative purposes and shows the classification of lenders into treatment and control groups based on their relative exposure to Hurricane Harvey through their loan and deposit portfolios. Orange shaded regions are FEMA declared counties, which are excluded from the sample. Blue-shaded regions are partitioned into four exposure quartiles based on $\text{Exposure}_c^{\text{Loc}}$. White counties have no data or are excluded.

Figure 10: 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. Vertical bars denote 95% confidence intervals.

Table 12: Hurricane Harvey Impact on Syndicated Loan Terms: Financial Firms

	(1) Margin	(2) No. Lenders	(3) Ln Amount	(4) Maturity
DID	109.808***	-4.948***	-0.462**	-11.748***
	(19.75)	(0.73)	(0.19)	(3.51)
Observations	1,841	1,841	1,841	1,834
R^2	0.630	0.839	0.602	0.560
County FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports Difference-in-Differences estimates for Hurricane Harvey for financial firms, using borrower exposure based on total property damage and comparing high-exposure counties (Q4) to the control group (Q1). Standard errors are clustered at the lender level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Hurricane Harvey Impact on Loan Terms: Non-Financial Firms

	(1) Margin	(2) No. Lenders	(3) Ln Amount	(4) Maturity
DID	10.109	1.828***	0.182	3.459
	(18.19)	(0.59)	(0.16)	(2.88)
Observations	4,549	4,549	4,549	4,536
R^2	0.675	0.748	0.661	0.512
County FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports Difference-in-Differences estimates for Hurricane Harvey for non-financial firms, using borrower exposure based on total property damage and comparing high-exposure counties (Q4) to the control group (Q1). Standard errors are clustered at the lender level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Sample Composition by Broad Industry Group and Exposure Quartile

Broad Industry Group	Q1 (Low)	Q2	Q3	Q4 (High)	Total
Banks	0	0	0	6	6
Corporates	2,253	412	1,516	2,142	6,323
Government	0	0	0	2	2
Media/Communications	61	156	0	130	347
Non-Bank Financials	308	5	232	1,244	1,789
Utilities	245	0	63	25	333
Total	**2,867**	**573**	**1,811**	**3,549**	**8,800**

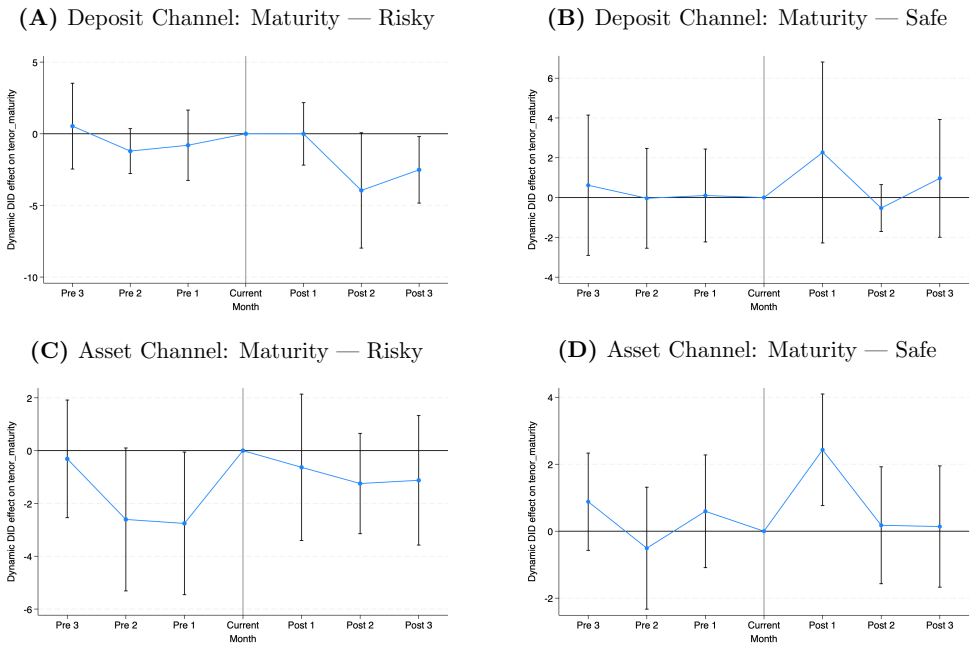
Notes: This table reports the frequency of observations by borrower broad industry group across exposure quartiles ($Q1$–$Q4$). The unit of observation is a tranche–lender pair from DealScan. The sample is restricted to the Hurricane Harvey event window (± 3 months from August 2017) and excludes counties directly affected by the hurricane or those with missing historical damage data. The final study sample consists of 8,800 observations.

Table 15: Hurricane Harvey Impact on Syndicated Loan Terms (Per Capita Exposure)

	(1) Margin	(2) No. Lenders	(3) Ln Amount	(4) Maturity
DID	64.871***	-1.827***	-0.259*	-2.831
	(16.37)	(0.53)	(0.14)	(1.91)
Observations	6,250	6,250	6,250	6,230
R^2	0.607	0.661	0.613	0.473
County FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

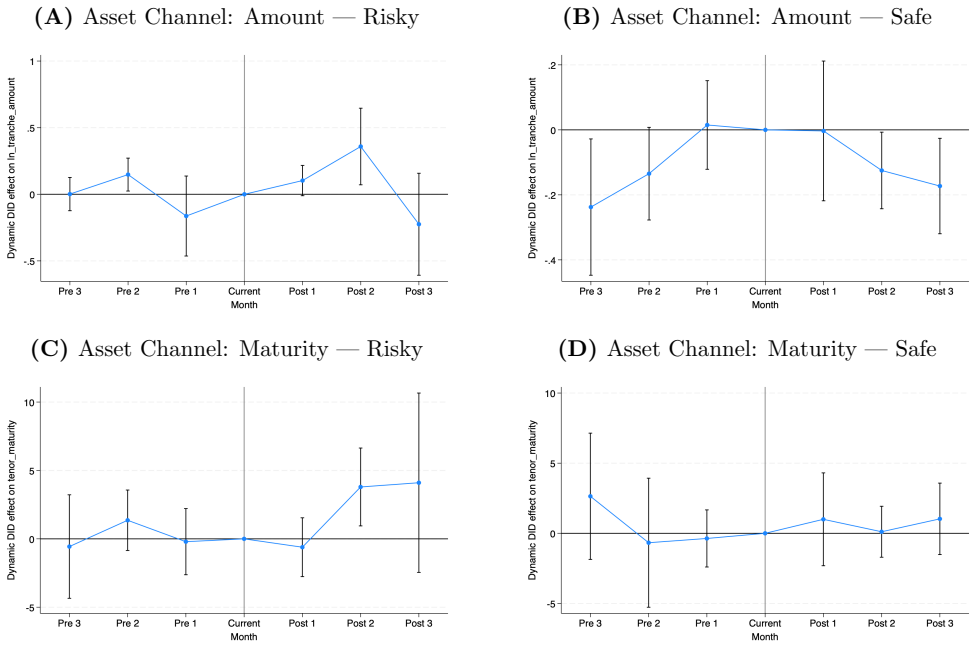
Notes: This table reports Difference-in-Differences estimates for Hurricane Harvey using county-level hurricane exposure measured by historical property damage per capita. The treatment group includes borrowers located in high-exposure counties (Q4), while the control group includes borrowers in low-exposure counties (Q1). Standard errors are clustered at the lender level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 11: Bank Subsample: Impact on Maturity (Affected Deposit/Asset Channel)



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey for the bank subsample. The outcome variable is loan maturity (months) at the tranche level. The top row uses deposit-channel exposure; the bottom row uses asset-channel exposure. 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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.

Figure 12: NonBank Subsample: Impact on Amount and Maturity (Asset Channel)



Notes: This figure presents event-study estimates from a dynamic difference-in-differences specification around Hurricane Harvey for the nonbank subsample. The outcome variables are log tranche amount (top row) and loan maturity in months (bottom row), based on asset-channel exposure. 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 hurricane month, so all coefficients are measured relative to the current month. Vertical bars denote 95% confidence intervals.