From Disaster to Debt: Exploring the Link Between Natural Catastrophes and Syndicated Loans*

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Abstract

How do syndicated loan markets reallocate credit when natural disasters strike? We develop a formal model of three-party coordination and provide empirical evidence using firm–bank–county–month data spanning 1982–2021. We make three contributions. First, we demonstrate theoretically that triadic relationships—spanning borrowers, lead arrangers, and participant lenders—are necessary for efficient credit allocation under information asymmetry. Bilateral relationships alone create hold-up problems and adverse selection, but their interaction resolves these frictions through credible signaling and cross-monitoring. Second, our empirical analysis confirms these predictions: bilateral relationships individually impede lending (participant-lead ties reduce lending share by 14.48%, borrower-lead ties by 22.82%), but their interaction increases lending share by 23.40%—effects approximately 20 times larger than direct disaster impacts—and reduces spreads by 3.86%. Third, we characterize a market failure where competitive equilibrium systematically under-allocates credit to disaster regions, and show that public assistance partially corrects this inefficiency: moving from the 10th to 90th percentile of FEMA aid reduces the misallocation gap by 24%. Our findings reveal that relationship capital in syndicates operates as a network asset requiring coordination across all parties, with implications for financial stability policy as climate-related disasters intensify.

Keywords: Syndicated Lending, Natural Disasters, Credit Allocation, Relationship Lending, Bank Risk

JEL Classifications: G21, G32, Q54, O16, L14

*We are grateful to Ihsan Badshah (discussant), John Gould, Zhangxin (Frank) Liu (discussant), and the participants at the 37th Asian Finance Association Annual Conference, the 2nd Western Australia's PhD Students Symposium in Accounting & Finance (WAPS 2025) and seminar participants at Curtin University.

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1. Introduction

Natural disasters destroy capital and disrupt production, creating urgent financing needs in affected regions. How do syndicated loan markets—where credit allocation requires coordination among borrowers, lead arrangers, and multiple participant lenders—respond to such shocks?[1] While prior research shows that credit reallocates toward disaster-affected regions (Ivanov et al., 2022), two fundamental questions remain: *How* does this reallocation occur within complex multi-party lending networks, and *why* do some firms maintain credit access during disasters while others are severely rationed? We address these questions by developing a formal theoretical framework and providing novel empirical evidence that *triadic relationships* among borrowers, lead arrangers, and participant lenders sustain credit flows under stress—but only when all three parties share established connections.

We make three primary contributions. First, we develop a formal model of syndicated lending under disaster shocks that identifies the specific coordination mechanism enabling credit reallocation. The model shows that bilateral relationships between any two parties can be individually detrimental (due to hold-up problems and information asymmetries), yet their interaction produces powerful complementarities through credible signaling and cross-monitoring. This insight reconciles previously contradictory findings in the relationship lending literature and yields testable predictions about credit allocation and pricing under stress.

Second, using firm–bank–county–month data spanning 1982–2021, we provide comprehensive empirical evidence for the triadic coordination mechanism. Consistent with our model's predictions, bilateral relationships in isolation impede lending—participant–lead ties reduce a bank's syndication share by 14.48%, and borrower–lead ties reduce it by 22.82%, reflecting hold-up problems and information gaps. However, when both types of relationships are strong, their *interaction* has a powerful positive effect: a one-standard-deviation increase in triadic relationship strength increases a lender's share of credit by 23.4% and reduces loan spreads by 3.86% (relative to their means). This triadic effect is approximately *nearly 20 times* larger than the direct impact of a disaster shock (1.26%), explaining the pronounced heterogeneity in credit access across firms during disasters.

Third, we show that competitive credit markets systematically under-allocate capital to disaster regions, and that public assistance can partially correct this market failure. Our model characterizes a wedge between the competitive equilibrium and the social optimum, driven by risk premia that banks internalize but a social planner would not. Empirically, we find that moving from the 10^{th} to the 90^{th} percentile of FEMA disaster relief reduces the credit misallocation by about 24%, providing micro-level evidence for the

[1] Figure A.1 in the Online Appendix illustrates the growth of syndicated lending over time, particularly since the early 1990s. The global financial crisis demonstrated this market's vulnerability, with syndicated lending declining 47% in 2008:Q4 and 79% from 2007:Q2 levels (Ivashina and Scharfstein, 2010).

capital reallocation channel underlying the "build back better" phenomenon documented by Tran and Wilson (2025).

Our theoretical framework extends existing relationship lending models in two important ways. First, we generalize bilateral relationship models to a syndicated setting where three distinct parties must coordinate under asymmetric information. Classic models focus on two-party relationships—for example, borrower–bank ties (Boot and Thakor, 1994; Petersen and Rajan, 1995) or lead–participant ties (Li, 2018)—but in syndicated markets these bilateral ties introduce distinct frictions (borrower–lead information asymmetry and lead–participant moral hazard) that cannot be resolved in isolation. Triadic coordination is *necessary*: strong borrower–lead relationships enable information acquisition, strong participant–lead relationships enable credible signaling, and only their combination allows information to flow credibly across the entire syndicate.

Second, we provide microfoundations for relationship capital in a dynamic setting with repeated interactions and Bayesian learning. Borrower–lead relationship capital emerges from self-enforcing information-sharing arrangements, wherein both parties have incentive to cooperate over time. Participant–lead relationship capital builds through reputation: participants observe loan performance and update their beliefs about the lead's honesty using Bayes' rule. These microfoundations justify treating relationship variables as predetermined in our empirical design, since relationship capital is accumulated over years of prior interactions rather than being determined by current loan terms.

Our model yields four testable predictions. *First*, disasters raise local credit demand if productivity gains from replacing destroyed capital outweigh the increase in default risk, leading to greater lending in affected areas. *Second*, binding bank balance-sheet constraints force lenders to reallocate credit, creating spillover effects in unaffected but connected markets. *Third*, bilateral relationships alone tend to reduce credit supply (due to hold-up problems), but strong bilateral ties in both dimensions together increase supply via complementary information and signaling effects. *Fourth*, the competitive equilibrium under-provides credit to disaster regions, but public assistance partially mitigates this under-allocation by reducing lenders' effective risk premia.

These results are not obvious without formal modeling. For instance, why would stronger bank–firm relationships ever reduce lending? Our framework provides the intuition: if a lead arranger has a strong relationship with the borrower but weak ties to participants, the lead gains valuable private information but cannot credibly convey it. Participants then fear adverse selection—the lead might retain high-quality loans and syndicate only weaker exposures—so they demand higher spreads or withdraw, ultimately restricting credit despite the strong borrower–lead relationship. Conversely, if participant–lead ties are strong but borrower–lead ties are weak, participants trust the lead's general ability but the lead lacks firm-specific knowledge, leaving high uncertainty. Only when both relationship dimensions are strong can the lead both acquire superior information and credibly transmit it to participants, thereby sustaining lending under stress.

Our study is distinct from three closely related strands of literature. *First*, we complement recent work on disaster-related credit reallocation (e.g., Koetter et al., 2020; Brown et al., 2021; Ivanov et al., 2022) by asking a fundamentally different question. Ivanov et al. (2022) use U.S. regulatory loan data to document that bank lending networks reallocate credit toward disaster-hit areas, Brown et al. (2021) show that banks accommodate borrowers after extreme weather shocks (often through emergency credit lines at higher rates), and Koetter et al. (2020) find that regional banks in Germany increase lending to firms affected by a major flood. These studies establish that credit flows respond to disaster shocks, but they do not identify *how* multi-bank networks coordinate those responses. In contrast, we focus on the syndicate-level mechanism: our model and evidence pinpoint a triadic coordination channel that enables syndicates to form and extend credit under extreme stress. Moreover, unlike regulatory data used by Ivanov et al. (2022), our detailed loan-level dataset (DealScan) provides rich information on contract terms and relationship structures. This granularity allows us to analyze the credit allocation mechanism itself. In addition, DealScan's monthly frequency allows us to observe short-term credit adjustments following disasters that annual data could miss.[2]

Second, we contribute to the relationship lending literature by demonstrating the need for coordination across all three parties in a lending syndicate. Prior studies on syndicated loans often emphasize either borrower–lead ties (Bharath et al., 2011; Schwert, 2018) or lead–participant ties (Li, 2018) in isolation. By examining each link separately, these papers overlook the interaction effect that we uncover: in a syndicate, relationship capital functions as a *network asset* that only fully realizes its value when borrower, lead, and participant are all strongly connected. Our findings show that two-party relationships, while beneficial in some contexts, can also create frictions (hold-up problems or informational silos) that only a well-connected triad can overcome.

Third, we add to the literature on disaster recovery and climate-related finance

[2]The SNC dataset provides detailed supervisory information on large syndicated loans but is not publicly available for research. Consequently, consistent with prior studies such as Berg et al. (2017); Kim et al. (2025); Green and Vallee (2025); Fleckenstein et al. (2025), we rely on the DealScan database, the leading public source for syndicated lending. Beyond its accessibility, DealScan contains richer information on loan pricing, maturity structure, collateralization, covenants, and syndicate composition—features not available in SNC data and essential for analyzing credit allocation mechanisms. We acknowledge that DealScan offers incomplete coverage of syndicate participant identities and share allocations, as noted in Bord and Santos (2012). However, in our sample, only 2.9% of participant-level observations lack identity information, and both lender and parent identifiers are complete throughout. Moreover, the incidence of missing syndicate shares is not systematically correlated with key loan or borrower characteristics, consistent with prior validation studies comparing DealScan and SNC coverage. Thus, while DealScan lacks the supervisory precision of the SNC data, its comprehensive contractual detail and monthly granularity enable analysis of within-region heterogeneity and short-term credit adjustments that cannot be observed in regulatory datasets.

by uncovering a micro-level mechanism that underpins "build back better" outcomes. For example, Tran and Wilson (2025) show that disaster-hit regions often experience above-trend economic growth during the reconstruction period, implying that infusions of public and private capital can more than offset the initial destruction. We provide the complementary micro-level evidence: robust lending networks—where firms, lead banks, and participant lenders have pre-established relationships—facilitate the efficient reallocation of capital needed for recovery. In doing so, we highlight a specific market failure (credit under-supply to disaster areas due to risk pricing) and show how public relief funds crowd-in private lending to partially correct it.

Empirically, we use the U.S. loan-level dataset covering four decades (1982–2021) to test our model's predictions. We first confirm that credit supply increases significantly in disaster-affected counties and contracts in connected (unaffected) counties, confirming the reallocation patterns documented by prior work (Cortés and Strahan, 2017; Ivanov et al., 2022). We then show that the strength of triadic relationships is the key factor explaining which firms continue to receive credit: lenders with strong borrower–lead–participant ties sustain lending, whereas those relying on only one relationship dimension retrench. Finally, we demonstrate that greater FEMA aid is associated with a smaller credit shortfall in disaster-hit areas, consistent with public funds mitigating the identified market failure. We address potential endogeneity concerns with several strategies, including a jackknife instrumental variables estimator to mitigate bias from many weak instruments, Lewbel (2012) heteroscedasticity-based internal instrumental variables, placebo tests and sensitivity analyses using Cinelli and Hazlett (2020). Our results are robust to excluding the largest disaster (Hurricane Katrina) and to a wide array of alternative specifications.

The rest of the paper is organized as follows. Section 2 develops the theoretical framework and derives our main hypotheses. Section 3 describes the data sources, variable construction, and summary statistics. Section 4 presents the empirical strategy and results, from baseline credit patterns to the triadic coordination tests and the impact of public assistance. Finally, Section 5 concludes with implications for financial intermediation theory and climate-related financial regulation.

2. Theoretical Framework and Hypotheses

This section develops a framework for understanding how natural disasters affect credit allocation in syndicated loan markets. We focus on two key channels: increased credit demand from capital destruction and coordination frictions within multi-party lending syndicates. From this framework, we derive testable hypotheses about direct disaster effects, spillover effects, triadic relationship mechanisms, and the role of public assistance. Formal derivations and proofs appear in the Online Appendix (Appendix B), with the mapping between theoretical propositions and empirical hypotheses summarized in Table B1.

2.1. *Disaster Shocks and Credit Demand*

A syndicated loan to firm i in county k involves three parties: the borrower seeking financing I_i, the lead arranger j who screens and structures the loan while retaining share $\alpha \in (0,1)$, and participants who provide the remaining $(1-\alpha)I_i$. Natural disasters of intensity $\delta_k \in [0,1]$ destroy capital, raising the marginal product of capital due to diminishing returns. Firms optimally respond by seeking external financing to restore productive capacity. Let I_i^* denote optimal investment. Capital destruction creates investment demand: $\partial I_i^*/\partial \delta_k = \bar{K}_i > 0$, where $\bar{K}_i$ is pre-disaster capital.

Banks allocate limited credit supply across regions by equalizing risk-adjusted returns. Let s_{ijk} denote bank j's lending share to firm i in county k. The bank faces interest rate r_i determined by the borrower's marginal product of capital, risk premium ρ_{ik}, and convex lending costs. The risk premium depends on disaster intensity and relationship capital: $\rho_{ik} = \rho_0 + \lambda \cdot \delta_k - \gamma \cdot R_{ijk}$. Higher disaster intensity raises perceived default risk ($\lambda > 0$) while stronger relationships reduce information asymmetry ($\gamma > 0$). Whether banks reallocate credit toward disaster regions depends on which effect dominates. If the marginal product effect exceeds the risk premium increase ($\partial r_i/\partial \delta_k > \lambda$), then net risk-adjusted returns ($r_i - \rho_{ik}$) rise, inducing banks to increase s_{ijk}.

The Online Appendix formalizes this intuition through a Cobb-Douglas production framework with disaster-induced capital destruction (Appendix B, Section A.1). When disasters destroy fraction δ_k of capital stock, diminishing returns imply $\partial MPK_k/\partial \delta_k > 0$ (Equation B4). Banks maximize risk-adjusted returns subject to portfolio constraints, generating the allocation condition in Equation B14. Proposition 1 demonstrates that credit reallocates toward disaster regions when productivity effects dominate risk effects, yielding our first hypothesis:

Hypothesis 1. *Property damage exposure is positively associated with syndicated lending share in disaster-affected counties.*

Theoretical Foundation: Proposition 1 in Appendix B.

Disaster-induced demand pressures also affect loan pricing. With relatively inelastic short-run credit supply, elevated demand exerts upward pressure on interest rates. The zero-profit condition for competitive lenders requires $r_i = r_f + \rho_{ik}$ where ρ_{ik} increases with disaster intensity: $\partial \rho_{ik}/\partial \delta_k = \lambda > 0$ (Equation B11). This generates:

Hypothesis 2. *Property damage exposure is positively associated with loan spreads in disaster-affected counties.*

Theoretical Foundation: Equation B11 in Appendix B.

2.2. *Spillover Effects in Connected Markets*

Banks face binding credit supply constraints in the short run, captured by the portfolio constraint $\sum_{i,k} s_{ijk} = 1$. When disasters strike some counties, banks must reallocate portfolios by reducing lending elsewhere. This generates spillover effects in two dimensions: geographically, to counties sharing borders with disaster-affected areas, and financially, to counties where banks maintain lending relationships regardless of geographic proximity.

For financially connected counties—those where bank j lends but which are not directly disaster-affected—the binding constraint implies $\sum_k \partial s_{jk}/\partial PExposure_j = 0$. Since disaster-affected counties experience $\partial s_{jk}/\partial PExposure_j > 0$ from Hypothesis 1, connected but unaffected counties must have $\partial s_{jk'}/\partial PExposure_j < 0$ to satisfy the constraint. Proposition 2 in the Online Appendix formalizes this result, demonstrating that banks with greater disaster exposure necessarily reduce lending shares in unaffected counties.

Hypothesis 3. *Banks with greater disaster exposure reduce lending shares in unaffected but financially connected counties.*

Theoretical Foundation: Proposition 2 in Appendix B.

The effect on interest rates in spillover regions is theoretically ambiguous. From the supply side, credit contraction should put upward pressure on rates. However, demand-side forces may offset this: uncertainty about disaster propagation can induce firms to adopt "wait-and-see" behavior (Bloom et al., 2007), reducing investment demand in unaffected regions. The net effect depends on relative elasticities, which we leave as an empirical question.

Hypothesis 4. *The effect of spillover on interest rates in unaffected counties is ambiguous, depending on relative strength of supply contraction versus demand reduction.*

Theoretical Foundation: Section A.2.3 in Appendix B.

2.3. Triadic Coordination Beyond Bilateral Relationships

Natural disasters amplify information asymmetries because collateral destruction reduces observable signals of creditworthiness. Syndicated lending differs fundamentally from bilateral bank loans because it requires coordination among three parties: the borrower, the lead arranger, and multiple participant lenders. We model relationship capital along two dimensions: borrower-lead ties R_{ij}^{BL} measuring frequency of past syndications between firm i and lead j, and participant-lead ties R_j^{PL} measuring co-participation frequency with lead j. These relationships affect information production differently, creating coordination challenges.

When borrower-lead ties are strong but participant-lead ties are weak ($R_{ij}^{BL} \gg R_j^{PL}$), the lead accumulates valuable private information but cannot credibly communicate it to participants. Participants rationally fear adverse selection: the lead might retain high-quality loans and syndicate problematic ones. This hold-up problem causes participants to demand higher rates or refuse participation, reducing lending despite strong borrower-lead relationships (see the incentive compatibility constraint in Equation B18). Conversely, when participant-lead ties are strong but borrower-lead ties are weak ($R_{ij}^{BL} \ll R_j^{PL}$), participants trust the lead's general competence but the lead lacks firm-specific information. Post-disaster uncertainty about this specific borrower remains high.

Triadic relationships resolve these frictions through complementary channels. Strong borrower-lead ties enable superior firm-specific information acquisition (modeled through signal precision in Equation B2). Strong participant-lead ties allow credible signaling through reputation built over repeated interactions (reputation capital $\Omega_j(R_j^{PL})$ in Equation B18). The combination constrains opportunistic behavior through cross-monitoring and reputation discipline.

The Online Appendix (Section A.3) provides formal microfoundations through repeated-game equilibria. Section A.4.1 derives borrower-lead relationship capital from self-enforcing contracts (Equations B2–B14), while Section A.4.2 models participant-lead reputation through Bayesian updating (Equations B9–B14). Proposition 3 demonstrates that bilateral relationships may individually reduce credit supply due to hold-up problems, but their interaction increases credit supply through complementary information acquisition and credible signaling. The key insight is complementarity: $\partial^2 I/\partial R_{ij}^{BL}\partial R_j^{PL} = \beta_3 > 0$ (Equation B20).

Formally, total credit supply to firm i is:

$$I_i = I_0 + \beta_1 R_{ij}^{BL} + \beta_2 R_j^{PL} + \beta_3 (R_{ij}^{BL} \times R_j^{PL}) \tag{1}$$

We can derive sign predictions from the hold-up problem when R_{ij}^{BL} is high but R_j^{PL} is low: participants rationally reduce participation, implying $\beta_1 < 0$ in isolation. From the information gap when R_j^{PL} is high but R_{ij}^{BL} is low, uninformed lending remains risky, potentially implying $\beta_2 < 0$ in some contexts. However, the interaction coefficient $\beta_3 > 0$ because relationship dimensions are complementary in resolving information frictions.

Hypothesis 5a. *Borrower-lead and participant-lead relationships are individually negatively associated with lending share when examined in isolation.*

Hypothesis 5b. *The interaction between borrower-lead and participant-lead relationships is positively associated with lending share, with magnitude exceeding negative effects of bilateral relationships.*

Theoretical Foundation: Proposition 3 parts (i) and (ii) in Appendix B.

Similarly, loan pricing should reflect the reduction in information frictions achieved through triadic coordination. Proposition 4 demonstrates that the risk premium decreases with triadic relationship strength through three channels: lower screening costs, reduced information asymmetry, and lower monitoring costs. This generates:

Hypothesis 5c. *The triadic relationship interaction is negatively associated with loan spreads, reflecting reduced information frictions.*

Theoretical Foundation: Proposition 4 in Appendix B.

2.4. Market Failure and Public Assistance

Competitive credit allocation may differ systematically from the social optimum. A social planner maximizes total production value across all counties subject to the aggregate credit constraint, equating marginal products of capital: $MPK_k = MPK_{k'}\ \forall k, k'$ (Equation B23). Competitive banks, by contrast, equate risk-adjusted returns: $MPK_k - \rho_k - \kappa s_k = MPK_{k'} - \rho_{k'} - \kappa s_{k'}$ (Equation B14). The risk premium term $\rho_k - \rho_{k'}$ creates a wedge between private and social allocations.

For a disaster-affected county k with $\delta_k > 0$ and unaffected county k' with $\delta_{k'} = 0$, we have $\rho_k - \rho_{k'} = \lambda\delta_k - \gamma(R_k - R_{k'}) > 0$ assuming similar relationship capital across counties.[3] This positive wedge implies competitive equilibrium systematically under-allocates credit to disaster regions: $s_k^{CE} < s_k^{SP}$ (Theorem 1).

The misallocation gap is:

$$s_k^{SP} - s_k^{CE} = \frac{\lambda\delta_k - \gamma(R_k - R_{k'})}{|Y_k''| + |Y_{k'}''| + 2\kappa} \tag{2}$$

where Y_k'' denotes the second derivative of output with respect to capital (capturing diminishing returns) and κ represents convex adjustment costs. The gap increases with disaster intensity and decreases with relationship capital.

Public disaster assistance can partially correct this market failure by reducing the risk premium wedge. FEMA grants G_k to county k affect the risk premium through: $\rho_k(\delta_k, G_k, R_k) = \rho_0 + \lambda\delta_k - \gamma R_k - \xi G_k$ where $\xi > 0$ captures the risk-mitigation effect (Equation B31). These interventions reduce lenders' perceived default risk through cash flow stabilization, collateral restoration, infrastructure repair, and uncertainty reduction.

From Equation 2, public assistance reduces the gap: $\partial(s_k^{SP} - s_k^{CE})/\partial G_k = -\xi/(|Y_k''| + |Y_{k'}''| + 2\kappa) < 0$ (Proposition 5). However, public assistance provides only partial correction because: (i) it is an imperfect substitute for private risk-bearing ($\xi G_k < \lambda\delta_k$ for feasible G_k), (ii) relationship capital provides complementary but incomplete insurance, and (iii) binding credit constraints prevent full adjustment even if risk premia are eliminated.

Hypothesis 6. *FEMA public assistance reduces the gap between actual and socially optimal credit allocation in disaster-affected counties.*

Theoretical Foundation: Theorem 1 and Proposition 5 in Appendix B.

[3] Here R_k represents average relationship capital between firms in county k and their lenders, formally $R_k \equiv \frac{1}{N_k}\sum_{i\in k,j}(R_{ij}^{BL} + R_j^{PL})/2$ where N_k is the number of firm-bank pairs in county k.

2.5. Summary and Empirical Strategy

These hypotheses structure our empirical analysis in subsequent sections. Table B1 in the Online Appendix provides a comprehensive mapping between theoretical propositions and empirical hypotheses. The model generates specific predictions about signs, relative magnitudes, and interaction effects that we test using firm–bank–county–month data from U.S. syndicated loan markets spanning 1982–2021. Section 4 presents our empirical strategy, progressing from baseline disaster-credit relationships (Hypotheses 1–2) through spillover effects (Hypotheses 3–4) to the triadic coordination mechanism (Hypotheses 5a–5c) and public assistance (Hypothesis 6).

3. Sources of Data and Summary Statistics

Our primary data source is the Thomson Reuters DealScan database, which provides comprehensive information on syndicated loan contracts, including facility amounts, pricing terms, maturity structure, collateral requirements, covenants, and syndicate composition. In addition, we incorporate county-level natural disaster data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which offers detailed county-specific monthly disaster records. Our sample spans April 1982 through December 2021, dictated by data availability: syndicated loan records in DealScan begin in April 1982, while SHELDUS coverage extends through December 2021. We exclude loans to public administration entities (SIC codes 9111–9999) to focus on private-sector credit allocation. The final sample comprises 159,411 firm–bank–county–month observations, representing 11,040 unique borrowing firms and 1,753 distinct lead arrangers.

Table 1 presents summary statistics and definitions for key variables used in our analysis. The sample comprises 159,411 firm–bank–county–month observations over the period April 1982 to December 2021, with slightly fewer observations for interest rates (140,704) due to missing spread information for some facilities, and tenor maturity (151,811) due to incomplete maturity date records.

[Insert Table 1 here]

Our primary outcome variable, lending share, measures the percentage of bank j's total syndicated lending allocated to firm i in county k during month t. The mean lending share of 16.39% with standard deviation 29.09% indicates substantial heterogeneity in credit allocation across bank–borrower pairs. This dispersion reflects several features of syndicated lending documented in prior research: banks often specialize in particular industries or borrower types (Sufi, 2007), maintain concentrated relationships with core clients (Bharath et al., 2011), and exhibit skewed portfolio allocations where a small number of large commitments dominate total lending (Schwert, 2018). Interest rates are measured as the all-in-drawn spread, expressed in basis points (bps) above the base rate.

The mean spread of 162.7 bps with a standard deviation of 212.1 bps indicates substantial cross-sectional variation in loan pricing.

Property exposure, our key explanatory variable, has mean 0.002 and standard deviation 0.680. The near-zero mean reflects the infrequent occurrence of FEMA-declared disasters: in most county–month observations, banks face no disaster-related property damage in their lending regions. However, the large standard deviation—340 times the mean—indicates that when disasters occur, affected banks experience economically meaningful exposure. This lumpiness is consistent with the spatial and temporal concentration of natural disasters: catastrophic events are rare but severe, creating sharp discontinuities in bank-level risk exposure that provide identifying variation for our empirical tests.

Our relationship capital measures capture the strength of borrower–lead and participant–lead ties. Participant–lead relationship strength averages 0.934 with standard deviation 0.155, indicating that in most syndicates, participants have extensive prior co-participation history with the lead arranger. This high mean is consistent with the "club" nature of syndicated lending documented by Champagne (2014), where a relatively stable network of institutional lenders repeatedly transacts with the same lead arrangers. The low standard deviation suggests that most lead arrangers maintain established participant networks, with relatively few syndicates formed among parties without prior relationships.

In contrast, borrower–lead relationship strength averages just 0.083 with standard deviation 0.168, implying that only about 8% of a borrower's recent syndicated loans are arranged by the same lead bank. This substantially lower mean compared to participant–lead relationships reflects greater fluidity in borrower–arranger matching: firms frequently switch lead arrangers across financing rounds, either to access competitive pricing (Dass and Massa, 2011) or because different arrangers specialize in different loan types (Bharath et al., 2011). The higher coefficient of variation (SD/mean = 2.02 for borrower–lead versus 0.17 for participant–lead) indicates that borrower–lead relationships exhibit more heterogeneity, with some firms maintaining strong ties to specific arrangers while others frequently switch lenders.

The divergence between participant–lead and borrower–lead relationship measures has important implications for our triadic coordination hypothesis. If relationship capital operated solely through bilateral channels, we would expect both measures to be similarly distributed. Instead, the data reveal that while participant networks are stable and tightly connected (high mean, low dispersion), borrower–arranger relationships are more sporadic and heterogeneous (low mean, high dispersion). This asymmetry supports our theoretical framework: participants form cohesive networks through repeated interactions, but individual borrowers tap into these networks episodically. The triadic coordination mechanism thus operates by bridging stable participant–lead networks with more fluid borrower–lead connections, enabling information transmission across the full syndicate structure.

[Insert Figure 1 here]

[Insert Figure 2 here]

Figure 1 depicts the distribution of total property damage from FEMA-declared natural disasters across US counties between April 1984 and December 2021. The figure indicates that certain counties are disproportionately affected by natural disasters. Specifically, Figure 2 reveals that approximately 50% of the total property damage in the US is concentrated in just 14 counties. These counties are located within six states: California, Florida, Louisiana, Mississippi, New Jersey and Texas.

Beyond providing descriptive context, the geographic concentration of disasters validates our empirical design. The lumpiness of disaster exposure—both spatially (concentrated in 14 counties) and temporally (infrequent but severe events)—creates sharp discontinuities in bank-level risk exposure that approximate quasi-random treatment assignment. While disaster propensity varies predictably across regions (e.g., coastal counties face higher hurricane risk), the *timing* of specific events within disaster-prone regions is largely unpredictable, providing plausibly exogenous variation in credit supply shocks. Our identification strategy exploits this temporal unpredictability while controlling for spatial heterogeneity through county fixed effects, effectively comparing credit responses after disaster shocks.

4. Specification of Empirical Models and Results

Building on the theoretical framework in Section 2, this section presents our empirical strategy for testing how natural disasters affect syndicated lending markets. We begin by constructing a measure of bank exposure to disaster-induced property damage, then specify our baseline regression model and present results that test Hypothesis 1.

4.1. Measuring Property Exposure and Lending Share

Following Cortés and Strahan (2017), we use property damage as our primary measure of disaster severity. Property damage directly affects borrowers' productive capacity and financing needs, making it an ideal metric for capturing disaster exposure that aligns with our theoretical predictions about credit demand and supply responses.

We construct bank-level property exposure by weighting disaster-related property damage in each county by the bank's lending presence in that county, normalized by the bank's total lending. Formally, property exposure for bank j in county k at time t is defined as:

$$PExposure_{j,k,t} = \frac{PropertyDamage^{c}_{k,t} \times \left(\frac{Lending^{bc}_{j,k,t}}{Lending^{c}_{k,t}}\right)}{Lending^{b}_{j,t}} \times FEMA^{c}_{k,t} \tag{3}$$

where $PropertyDamage^{c}_{k,t}$ represents total property damage in county k at time t; $\frac{Lending^{bc}_{j,k,t}}{Lending^{c}_{k,t}}$ captures bank j's market share of lending in county k; and $Lending^{b}_{j,t}$ is bank j's total lending across all counties. The indicator variable $FEMA^{c}_{k,t}$ restricts our analysis to disasters declared by the Federal Emergency Management Agency (FEMA), consistent with prior studies (Cortés and Strahan, 2017; Bos et al., 2022; Correa et al., 2022; Curcio et al., 2023). This restriction ensures we focus on economically significant disasters that trigger federal emergency responses.[4]

Our dependent variable captures the concentration of bank lending to individual firms:

$$LendingShare^{fbc}_{i,j,k,t} = \left(\frac{Lending^{fbc}_{i,j,k,t}}{Lending^{b}_{j,t}} \right) \times 100 \tag{4}$$

where $LendingShare^{fbc}_{i,j,k,t}$ represents bank j's lending to firm i (located in county k) as a percentage of the bank's total lending portfolio at time t. This variable directly measures how banks reallocate credit across firms and regions in response to disaster shocks.

4.2. Baseline Regression Specification

Combining Equations 3 and 4, we specify our baseline model to test whether banks increase lending shares to firms in disaster-affected counties (Hypothesis 1):

$$LendingShare^{fbc}_{i,j,k,t} = \alpha\, PExposure_{j,k,t} + \boldsymbol{X^{l}_{t}}\boldsymbol{\beta} + \sum_{\lambda=1}^{5} \theta_{\lambda} + \delta_{T} + \epsilon_{i,j,k,t} \tag{5}$$

where α is our coefficient of interest, measuring how property exposure affects lending allocation. The vector $\boldsymbol{X}^{l}_{t}$ includes loan-level characteristics: the logarithm of the number of lenders in the syndicate, logarithm of loan maturity, and indicator variables for secured loans and covenant provisions. We include a comprehensive set of fixed effects denoted by θ_{λ}: firm, bank, county, firm-bank-county, and industry fixed effects. These fixed effects control for time-invariant heterogeneity across firms, banks, geographic regions, specific firm-bank relationships, and sectoral characteristics. Finally, δ_{T} represents year-month fixed effects that absorb common time-varying shocks, and $\epsilon_{i,j,k,t}$ is the error term.

This specification identifies the effect of disaster exposure on the lending share to the same firm following changes in local property damage. The rich set of fixed effects ensures that the estimates are not confounded by time-invariant differences across firms, banks, or locations, nor by aggregate trends that influence all lending decisions.

[4] To address potential endogeneity concerns that absolute property damage may reflect pre-disaster development levels rather than disaster severity, we re-estimated our baseline specification using three alternative normalizations: (i) property damage scaled by county-level personal income, (ii) per capita personal income, and (iii) per capita net earnings. Data come from the U.S. Bureau of Economic Analysis covering our full sample period. Across all normalizations, the estimated coefficients remain positive, statistically significant, and qualitatively consistent with baseline results. Complete results are available upon request.

4.3. Baseline Results

Table 2 presents estimates of Equation 5. Our results reveal a statistically significant positive relationship between property exposure and syndicated lending shares, consistent with both our theoretical predictions and prior empirical evidence on disaster-induced credit reallocation (Bos et al., 2022; Koetter et al., 2020; Ivanov et al., 2022).

[Insert Table 2 here]

Column (1) presents the most parsimonious specification with property exposure as the sole explanatory variable alongside the full battery of fixed effects. The coefficient estimate of 0.303 ($p < 0.06$) implies that a one standard deviation increase in property exposure raises the lending share by 30.3 percentage points, equivalent to a 1.26% increase relative to the sample mean.[5] This economically meaningful effect indicates that firms in counties experiencing greater property damage receive substantially larger shares of their lenders' portfolios, reflecting excess credit demand for reconstruction and recovery financing.

Column (2) augments the baseline specification with loan-level control variables. After including the logarithm of lender numbers, logarithm of tenor maturity, and indicators for secured status and covenants, the economic magnitude of the property exposure effect decreases slightly to 1.19%. The stability of the coefficient suggests that the property exposure is not materially confounded by loan characteristics, reinforcing confidence in our identification strategy.

Column (3) addresses concerns about the financial sector's unique role in disaster recovery. We exclude firms in the finance, insurance, and real estate sectors (SIC codes 6000–6799) to ensure our results are not driven by financial institutions' potentially idiosyncratic responses to disasters. The effect size remains nearly identical at 1.28%, demonstrating that our findings generalize beyond the financial sector. This consistency supports retaining the full sample in subsequent analyses, as sectoral composition does not meaningfully influence our conclusions.

These baseline results provide robust evidence supporting Hypothesis 1: banks systematically increase their lending shares to firms in disaster-affected counties. The positive reallocation effect reflects multiple economic forces highlighted in our theoretical framework. From the firm perspective, natural disasters disrupt operations, destroy capital stock, and deplete working capital, creating urgent financing needs to repair damaged assets, replenish inventories, and stabilize cash flows during recovery. From the bank perspective, established lenders have strong incentives to support existing borrowers'

[5] Economic magnitude is calculated as $\frac{0.303 \times 0.681}{16.385}$, where 0.681 is the standard deviation of property exposure and 16.385 is the mean lending share.

recovery efforts—both to protect their existing loan portfolios from default and to preserve valuable long-term lending relationships.[6]

The syndicated loan structure is particularly well-suited to financing disaster recovery. Unlike bilateral bank loans where a single lender bears all credit risk, syndicated loans distribute risk across multiple participating banks. This risk-sharing mechanism enables larger loan amounts than any individual bank would be willing or able to provide alone, while simultaneously reducing each lender's exposure to borrower-specific default risk. During the higher uncertainty following natural disasters, this collaborative structure allows banks to participate in recovery financing while maintaining prudent risk management—explaining why syndicated credit flows toward disaster-affected regions.[7]

The magnitude of our estimates aligns with findings from related literature. Bos et al. (2022) and Koetter et al. (2020) document similar increases in bank lending to disaster-affected regions, attributing the credit expansion to firms' recovery-related financing needs. Syndicate structures facilitate substantial credit flows to disaster-affected borrowers, suggesting that the benefits of risk-sharing outweigh any coordination frictions in this context.

4.4. Excluding Severe Natural Disasters

Hurricane Katrina represents the most extreme disaster in our sample, with estimated damages of US$201.3 billion (2024 dollars) and 1,833 fatalities.[8] To ensure our baseline results reflect generalizable disaster-response patterns rather than this singular extreme event, we conduct robustness checks excluding Katrina-affected counties for 6, 12, and 24 months post-disaster. We also exclude all US counties over the same windows to control for contemporaneous economic disruptions.

[Insert Table 3 here]

Table 3 reports results across these exclusion specifications. The property exposure coefficient remains positive and statistically significant at the 1% level in all cases, ranging narrowly from 0.285 to 0.289. This stability confirms that disaster-induced credit reallocation represents a consistent structural response across multiple events, not an isolated reaction to Hurricane Katrina.

[6] We further examine the role of relationship lending in Section 4.9, where we document that prior lending relationships are positively associated with higher post-disaster lending shares, consistent with relationship banking incentives.

[7] To verify that our baseline results are not sensitive to the temporal specification of disaster exposure, we re-estimated Equation 5 using alternative exposure windows: cumulative property damage over 3-, 6-, 9-, and 12-month periods, as well as one-period lagged exposure. In all cases, the estimated coefficients remain positive, statistically significant, and economically similar to Table 2. Complete results are available upon request.

[8] Damage estimates from the National Oceanic and Atmospheric Administration (NOAA). County lists obtained from the Missouri Department of Social Services (https://dssmanuals.mo.gov/). See also https://www.ncei.noaa.gov/access/billions/.

4.5. Spillover Effects in Neighboring Counties

Major disasters may generate spillover effects in adjacent counties through economic interdependencies and financial linkages (Barth et al., 2024; Bassetti et al., 2024; Giannetti and Saidi, 2019). Neighboring firms may experience increased demand as regional supply chains are disrupted, or may face reduced demand through negative spillovers, both creating financing needs.

We construct two measures of neighbor exposure using county adjacency data from the U.S. Census Bureau:[9]

$$PExposure^{sum}_{j,n,t} = \frac{Lending^{bc}_{j,k,t}/Lending^{c}_{k,t}}{Lending^{b}_{j,t}} \times \sum_{n=1}^{N} PropertyDamage_{n,t} \times FEMA_{n,t} \quad (6a)$$

$$PExposure^{mean}_{j,n,t} = \frac{Lending^{bc}_{j,k,t}/Lending^{c}_{k,t}}{Lending^{b}_{j,t}} \times \frac{\sum_{n=1}^{N} PropertyDamage_{n,t} \times FEMA_{n,t}}{N} \quad (6b)$$

where n indexes neighboring counties and N is the total number of neighbors for county k. Figure 3 illustrates this construction using Dallas County, Alabama, which has four FEMA-declared disaster neighbors. The sum measure aggregates total damage ($a+b+c+d$), while the mean measure computes average neighbor damage ($\frac{a+b+c+d}{4}$). Non-FEMA disasters (e.g., damage e in Lowndes County) are excluded.

[Insert Figure 3 here]

[Insert Table 4 here]

Table 4 presents estimates using both exposure measures in columns (1) and (2). Both coefficients are positive and statistically significant, confirming that disasters generate spillover effects extending beyond directly affected counties. The differing magnitudes reflect the construction methods—summed versus averaged neighbor damage—but both demonstrate that credit demand rises in unaffected counties when neighboring regions experience major disasters. These findings underscore the spatial interconnectedness of credit markets and suggest that disaster-induced financing needs propagate through regional economic networks.

4.6. Addressing Endogeneity

To mitigate concerns about endogeneity arising from unobserved confounders and finite-sample bias in the standard two-stage least squares (2SLS) framework, we employ

[9] Data collected from https://www.census.gov/en.html on November 30, 2024.

two complementary instrumental variables (IV) estimators: the Jackknife Instrumental Variables Estimator (JIVE2; Angrist et al. 1999) and Lewbel's heteroskedasticity-based IV approach (Lewbel 2012). Both estimators are increasingly used in applied empirical research in economics and finance (e.g., Wowak et al. 2025; Arcand et al. 2015; Luo et al. 2025; Duong et al. 2026 apply Lewbel IV, while Haggag et al. 2019; Lyu et al. 2025; Fu et al. 2022 employ Jackknife IV).

4.6.1. Jackknife Instrumental Variables Estimation

Standard 2SLS estimators can suffer from finite-sample bias when fitted values in the first stage are mechanically correlated with structural residuals, particularly in models with high-dimensional fixed effects and endogenous regressors such as *Property Exposure* (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). The JIVE2 estimator addresses this issue by constructing leave-one-out fitted values that remove the mechanical correlation between the instrument and the structural error term. Specifically, for observation i, the Jackknife instrument is computed as

$$\text{Jackknife IV (FEMA-MA)}_{i,t} = \frac{\hat{x}_i - h_i x_i}{1 - 1/N_{\text{eff}}},$$

where $\hat{x}_i$ denotes the first-stage fitted value, h_i the leverage from the corresponding regression, and N_{eff} the effective sample size. This adjustment corrects for finite-sample bias and improves estimator consistency relative to conventional 2SLS.

4.6.2. Lewbel Heteroskedasticity-Based Identification

Lewbel (2012) heteroskedasticity-based approach provides an alternative identification strategy when external instruments are unavailable or potentially weak. Unlike traditional IV estimation that relies on exclusion restrictions, this method exploits systematic heteroskedasticity in the structural errors to construct valid internal instruments.

Formally, consider the triangular system:

$$Y_1 = X'\beta_1 + Y_2\gamma_1 + \varepsilon_1 \tag{7}$$

$$Y_2 = X'\beta_2 + \varepsilon_2, \tag{8}$$

where Y_1 represents lending outcomes, Y_2 is the potentially endogenous regressor (*Property Exposure*), and X denotes exogenous covariates. The Lewbel estimator constructs instruments as $Z = [Z - E(Z)]\hat{\varepsilon}_2$, where Z is a subset of X (or all elements except the constant), and $\hat{\varepsilon}_2$ are estimated residuals from the first-stage regression of Y_2 on X.

In our setting, heteroskedasticity in ε_2 arises from regional variation in banks' exposure to disaster-prone counties, which induces differences in the *Property Exposure* measure through the geographic distribution of their lending portfolios.

4.6.3. Estimation Results

[Insert Table 5 here]

Table 5 reports the main results. Columns (1)–(2) present the JIVE2 first- and second-stage estimates, while Columns (3)–(4) display results from the Lewbel IV specification. We use a 10-year moving average of FEMA disaster declarations as an instrumental variable in the JIVE2 estimation.[10]

The first-stage diagnostics indicate strong instrument relevance in both cases. The F-statistic of excluded instruments in the Jackknife specification is 17.56 (well above the Stock-Yogo weak instrument threshold of 10), while the Lewbel specification exhibits even stronger first-stage performance with an F-statistic exceeding 999, reflecting the high precision of the heteroskedasticity-based instruments.

Across estimators, the coefficient on *Property Exposure* remains positive and highly significant. The JIVE2 estimate of 0.1825 (s.e. = 0.0629) is somewhat smaller than the Lewbel IV estimate of 0.2777 (s.e. = 0.0068), though both are economically significant and statistically indistinguishable from our baseline 2SLS estimates. The tighter standard errors in the Lewbel specification reflect the greater number of instruments generated through the heteroskedasticity-based approach. The Hansen J-test of overidentifying restrictions yields a test statistic of 3.561 with $p = 0.168$, failing to reject the null hypothesis that the instruments are valid. This provides additional support for the identifying assumptions.

Overall, both the Jackknife and Lewbel IV approaches mitigate endogeneity and finite-sample bias concerns, reinforcing the causal interpretation of disaster exposure effects on syndicated loan allocation. The Lewbel IV estimates are particularly valuable as they do not rely on the validity of external instruments and instead leverage the natural heterogeneity in banks' disaster exposure to achieve identification.

4.7. Exposure to Disasters and Interest Rates

We test Hypothesis 2 by re-estimating our baseline model with loan spreads as the dependent variable. Natural disasters surge credit demand as affected firms seek external financing for recovery. Given relatively inelastic short-run credit supply, excess demand exerts upward pressure on interest rates. We measure spreads as the premium charged above the base rate.

[10] Historical disaster patterns serve as valid instruments under conditions outlined by Angrist et al. (1996); Angrist and Krueger (2001) and Reed (2015). The instrument satisfies the *relevance condition* because historical disaster frequency strongly predicts current exposure due to persistent geographic and climatic vulnerabilities (Strobl, 2011). The *exclusion restriction* holds because, conditional on county and time fixed effects, historical patterns (averaged over the past decade) affect current lending only through current disaster exposure, not direct channels. Past disasters occurred years before current loan originations and do not directly influence syndicate formation, ensuring the instrument is predetermined relative to current outcomes.

[Insert Table 6 here]

Table 6 shows that property exposure coefficients are consistently positive and statistically significant, confirming lenders adjust pricing upward in response to disaster-induced loan demand. These findings align with Correa et al. (2022) and Javadi and Masum (2021), who document that climate-induced disasters widen loan spreads for firms in disaster-prone areas.

4.8. Credit Reallocation from Connected Markets

Hypotheses 3 and 4 predict that short-run credit supply constraints force banks to reallocate resources from unaffected regions, where the bank maintains active lending relationships, toward disaster-affected areas. While supply contraction in unaffected counties should increase interest rates, concurrent demand-side adjustments may offset this pressure. Specifically, firms may adopt "wait-and-see" strategies and defer investment during periods of heightened uncertainty (Stokey, 2016; Bloom et al., 2007), dampening credit demand. The net effect on interest rates in unaffected but financially connected markets is therefore theoretically ambiguous.

To test these predictions, we construct bank-level disaster exposure aggregated across all counties where bank j lends:

$$PExposure_{j,t} = \frac{\sum_{k=1}^{n} \left(PropertyDamage_{k,t}^{c} \times Lending_{j,k,t}^{bc} \times FEMA_{k,t}^{c}\right)}{Lending_{j,t}^{b}} \tag{9}$$

Higher values of $PExposure_{j,t}$ indicate greater involvement in disaster-affected lending markets. We estimate the following specifications for unaffected counties:

$$LendingShare_{i,j,k,t}^{fbc} = \alpha_4 PExposure_{j,t} + \boldsymbol{X_t^l \Gamma_1} + \sum_{\lambda_4=1}^{5} \theta_{\lambda_4} + \delta_{T_4} + \varepsilon_{i,j,k,t} \tag{10a}$$

$$InterestRate_{i,j,k,t}^{fbc} = \alpha_5 PExposure_{j,t} + \boldsymbol{X_t^l \Gamma_2} + \sum_{\lambda_4=1}^{5} \theta_{\lambda_4} + \delta_{T_4} + \varepsilon_{i,j,k,t}^{'} \tag{10b}$$

where $\boldsymbol{X}_t^l$ includes loan-level controls and θ_λ represents firm, bank, county, firm-bank-county, and industry fixed effects. Hypothesis 3 predicts $\alpha_4 < 0$: banks reduce lending shares in unaffected counties as they reallocate capital toward disaster regions. Hypothesis 4 leaves the sign of α_5 ambiguous, as it depends on the relative strength of supply contraction versus demand reduction.

To cleanly identify the reallocation channel, we exclude all firm-county-month observations directly exposed to disasters and restrict the sample to banks that actively lend to disaster-affected counties during the study period.

[Insert Table 7 here]

Table 7 provides compelling evidence of spatial credit reallocation. Column (1) shows that bank-level disaster exposure is negatively and significantly associated with lending shares in unaffected counties. A one standard deviation increase in $PExposure_{j,t}$ reduces lending shares by 1.73% relative to the mean, confirming that banks systematically contract credit supply in unaffected markets to support lending in disaster-hit regions.

Column (2) examines interest rate responses. Contrary to simple supply-side predictions, we find no statistically significant change in loan spreads within unaffected regions. Two mechanisms may explain this null result. First, firms in unaffected counties may reduce investment demand due to disaster-induced economic uncertainty, offsetting supply-driven upward pressure on rates. Second, disaster shocks in geographically distant counties may not materially affect the marginal product of capital in unaffected regions, limiting the transmission of credit supply shocks to local borrowing costs.

These findings support our theoretical framework's prediction of interregional credit reallocation while highlighting the importance of demand-side adjustments in determining equilibrium interest rate responses in financially connected but undamaged markets.

4.9. Triadic Relationship Networks in Syndicated Lending

One of the main contributions of this paper identifies triadic relationships as the mechanism enabling credit reallocation during disasters. Unlike bilateral relationship lending documented in traditional banking (Petersen and Rajan, 1995; Berger and Udell, 1995), syndicated lending requires coordination among three parties: borrowers, lead arrangers, and participant lenders. We argue that relationship capital in syndicates operates as a network asset rather than a sum of bilateral connections.

Prior research examines bilateral dimensions in isolation. Bharath et al. (2011) and Schwert (2018) analyze borrower-lead ties; Sufi (2007) examines how borrower opacity affects participant allocations; Li (2018) documents participant-lead effects on pricing. However, examining each dimension separately misses a critical insight: bilateral ties can simultaneously create hold-up problems (Sufi, 2007; Corwin and Schultz, 2005) yet facilitate efficient allocation when properly coordinated across the full syndicate network.

We test this using two relationship measures. *Borrower-Lead Relationship* equals the number of syndicated loans between firm i and lead arranger j in the prior three years, divided by firm i's total syndicated loans during that period. *Participant-Lead Relationship* equals the average number of times current participants co-participated with lead j in the prior three years, divided by the number of participants in the current syndicate. Their interaction captures triadic network strength spanning all three parties.

[Insert Table 8 here]

Table 8 presents results using continuous relationship measures (columns 1–2) and categorical measures constructed by median splits (columns 3–4). The continuous specification reveals that bilateral relationships individually reduce lending shares: participant-lead ties reduce lending by 14.48% relative to the mean, while borrower-lead ties reduce it by 22.82%, consistent with hold-up problems and information asymmetries predicted by Hypothesis 5a. However, the interaction term is positive and economically large: a one standard deviation increase in triadic relationship strength increases lending share by 23.40%, supporting Hypothesis 5b. This triadic effect is approximately almost 20 times larger than the direct disaster exposure effect (1.26% from Table 2), demonstrating that network coordination dominates disaster-induced demand shocks in determining credit allocation.

The categorical specification (columns 3–4) validates this interpretation and reveals the underlying pattern more transparently. Relative to firms with both relationships below median (baseline), three distinct effects emerge. First, firms with strong participant-lead ties only receive 23.88% more credit, reflecting reputational benefits of established arranger-participant networks. Second, firms with strong borrower-lead ties only receive 2.22% *less* credit, confirming that concentrated borrower-lead relationships without participant network support create hold-up problems. Third, firms with both relationships above median—the triadic structure—receive 28.45% more credit, representing a 19% improvement over participant networks alone (28.45% versus 23.88%) and dominating all other configurations. This ordering—triadic (28.45%) > participant-only (23.88%) > baseline (0%) > borrower-only (−2.22%)—directly confirms that network-wide coordination is essential for efficient credit allocation.

For spreads, results support Hypothesis 5c. The continuous specification (column 2) shows that a one standard deviation increase in participant-lead ties reduces spreads by 6.15 basis points (3.85% of the mean), while a one standard deviation increase in borrower-lead ties *increases* spreads by 11.75 basis points (7.36% of the mean), and the triadic interaction reduces spreads by 11.77 basis points (7.37% of the mean). The net effect in fully connected triadic networks is a 6.17 basis point reduction (3.86% of the mean). The categorical results (column 4) indicate that all relationship configurations reduce spreads relative to the baseline: triadic networks reduce spreads by 12.94 basis points (8.10% of the mean), participant-only networks reduce spreads by 11.52 basis points (7.21% of the mean), and borrower-only networks reduce spreads by 3.64 basis points (2.28% of the mean). The triadic configuration achieves the largest spread reduction, demonstrating that network-wide coordination most effectively reduces pricing frictions.

These findings demonstrate that relationship capital in syndicated lending differs fundamentally from bilateral banking relationships. Bilateral ties alone are insufficient or counterproductive for credit allocation: isolated participant-lead networks provide substantial quantity benefits (23.88% more credit), but isolated borrower-lead relationships impose quantity costs (−2.22% less credit). However, both bilateral configurations reduce spreads relative to having no relationships (11.52 bps and 3.64 bps respectively), indicating that even problematic relationships for quantity allocation provide some pricing benefits through reduced information asymmetry. Only triadic coordination—where all three parties maintain established connections—generates maximum benefits on both dimensions: 28.45% more credit and 12.94 basis points lower spreads (8.10% of the mean). The mechanism operates through three complementary channels: borrower-lead ties enable firm-specific information acquisition critical when disasters destroy observable collateral; participant-lead ties allow credible signaling of this information through reputation; and their combination constrains opportunistic behavior through cross-monitoring and reputation discipline. The fact that triadic effects in the continuous specification only partially offset combined bilateral quantity negatives (23.40% versus 37.30%, recovering 63% of frictions) while generating substantial spread reductions (6.17 bps net effect, with triadic configuration achieving 12.94 bps reduction) highlights that network coordination operates through distinct channels for quantities versus prices. This explains why only firms with sufficiently strong network-wide coordination maintain robust credit access at favorable terms during disasters, contributing to observed heterogeneity in firm resilience.

4.10. FEMA Public Assistance and Risk-Adjusted Credit Misallocation

As discussed in Section 2.4, disaster-sensitive risk premia may induce banks to under-allocate credit relative to the social optimum. To test this mechanism empirically, we construct a county-month measure of the credit misallocation gap, the difference between expected allocation based on local disaster intensity and realized lending:

$$\ln(\text{Misallocation})_{k,t} = [\ln(\text{PropertyDamage})_{k,t} - \ln(\text{Lending})_{k,t}] \times \text{FEMA}_{k,t}$$

where k and t denote county and year-month, respectively. The measure equals zero in non-disaster months, ensuring it captures disaster-induced deviations from required credit allocation.

To isolate the effect of external fiscal support, we compute the three-month moving average of log-transformed FEMA public assistance for each county, lagged one month to mitigate simultaneity with contemporaneous lending decisions. The moving average captures persistent support while smoothing monthly volatility. We estimate:

$$\ln(Misallocation)_{k,t} = \beta_0 + \beta_1 \ln(PublicAssist)^{3mMA}_{k,t-1} + \boldsymbol{X}^l_t\Gamma + \sum_{\lambda=1}^{5} \theta_\lambda + \delta_T + \varepsilon_{i.j,k,t} \quad (11)$$

where $\boldsymbol{X}^l_t$ includes loan-level controls (lender numbers, loan tenor, secured status, covenants), $\sum_{\lambda=1}^{5} \theta_\lambda$ denotes firm-bank-county, firm, bank, county, and industry fixed effects, and δ_T controls for year-month fixed effects.

[Insert Figure 4 here]

Figure 4 plots the marginal effect of FEMA public assistance on the misallocation gap. The horizontal axis represents the three-month moving average of log public assistance; the vertical axis measures the reduction in the misallocation gap. Marginal effects are estimated from Equation 11 with standard errors clustered at the firm-bank-county level.[11] The figure reveals a monotonic decrease in the misallocation gap as public assistance increases. Moving from the 10th to the 90th percentile of the public assistance distribution reduces the misallocation gap by approximately 24% of its mean value, demonstrating that exogenous FEMA support systematically mitigates inefficient credit allocation in disaster-affected counties. This finding provides strong empirical support for Hypothesis 6, i.e., public assistance can partially offset bank underallocation induced by disaster-driven risk premia.

4.11. Heterogeneity Analysis

We examine heterogeneity in disaster-credit relationships across disaster types, regional exposure frequency, and firm-loan characteristics.

4.11.1. By Disaster Type

Table 9 examines whether property exposure effects differ across major disaster types—fire, flood, and hurricane—which account for 93.44% of FEMA-declared events in our sample.[12] We interact property exposure with disaster-type indicators. Columns (1)–(3) present separate estimates; column (4) includes all interactions jointly.

[Insert Table 9 here]

All disaster types generate positive, significant effects on lending share. A one standard deviation increase in exposure increases lending share by 0.68% (fire), 1.29% (flood), and 1.19% (hurricane) relative to their means. The larger flood effect is consistent with greater infrastructure damage and longer recovery horizons. Coefficients remain stable in the joint specification.

4.11.2. By Regional Disaster Frequency

Figure 2 shows that 50% of total property damage during our sample period occurred in 14 counties across six states: California, Florida, Louisiana, Mississippi, New Jersey, and Texas. We classify these as *disaster-prone* counties; all others are *non-disaster-prone*.

[11] Predicted margins and confidence intervals are computed using the delta method. The one-month lag ensures that public assistance is predetermined relative to lending decisions.

[12] Respective shares are 23.95% (fire), 6.88% (flood), and 62.61% (hurricane). "Hurricane" includes Coastal Storm, Hurricane, Severe Ice Storm, Severe Storm, Snowstorm, and Tornado; "Flood" includes Dam/Levee Break and Flood.

Table 10 shows that while lending shares respond positively to disasters in both groups, sensitivity is lower in disaster-prone regions. This likely reflects adaptive strategies developed by frequently affected firms, reducing post-disaster credit adjustments.

[Insert Table 10 here]

4.11.3. By Loan and Firm Size

Table 11 examines variation by loan and firm size. Smaller loans exhibit substantially greater sensitivity to disaster exposure than larger loans, suggesting firms seeking smaller financing amounts rely more heavily on post-disaster syndicated lending. Similarly, smaller firms show higher sensitivity than larger firms, consistent with larger borrowers' greater financial resilience, stronger credit ratings, and access to alternative financing sources. These patterns align with evidence that small firms face more severe disaster-induced credit constraints (Cortés and Strahan, 2017; Ivanov et al., 2022), underscoring syndicated lending's role in supporting financially constrained borrowers during disasters.

[Insert Table 11 here]

4.12. Robustness Analysis

4.12.1. Sensitivity to Omitted Variable Bias

We assess robustness to omitted variable bias following Cinelli and Hazlett (2020), which quantifies how strongly a hypothetical unobserved confounder would need to correlate with both treatment (property exposure) and outcome (lending share) to materially alter estimates. The approach expresses confounding strength in terms of partial R^2 values, enabling direct evaluation of alternative confounding scenarios.

[Insert Figure 5 here]

Figure 5 presents contour plots. The horizontal axis shows the confounder's partial R^2 with treatment; the vertical axis shows its partial R^2 with outcome. Contours represent the adjusted coefficient on property exposure that would obtain if a confounder of given strength were included. Panel (5a) shows how the point estimate would change if we included a hypothetical confounder as strong as the loan controls (lender count, maturity, secured status, covenants). Panel (5b) shows how the t-value would change.

A confounder one to three times stronger than loan controls would reduce the property exposure coefficient from 0.27 to 0.23, with t-values varying from 4.31 to 3.73. Even with a confounder three times more powerful, the estimate (0.23) remains close to the baseline (0.285), indicating robustness to omitted variable bias.

4.12.2. Placebo Analysis

We conduct a placebo test by randomly generating property exposure values from the sample distribution. Table 12 reports average coefficient estimates across 1,000 replications. The resulting coefficients are economically negligible and statistically insignificant across all specifications, confirming that baseline findings are not driven by spurious correlations.

[Insert Table 12 here]

5. Conclusion

This paper makes three contributions to understanding credit allocation in syndicated loan markets during natural disasters. First, we develop a formal theoretical framework demonstrating that triadic relationships—spanning borrowers, lead arrangers, and participant lenders—are necessary for efficient credit allocation under information asymmetry. Our model shows that bilateral relationships alone create hold-up problems and adverse selection, but their interaction resolves these frictions through credible signaling and cross-monitoring. The model generates testable predictions about credit quantities, loan pricing, spillover effects, and market failure that we validate empirically. Second, using firm–bank–county–month data spanning 1982–2021, we provide comprehensive empirical evidence confirming these theoretical predictions: bilateral relationships individually impede lending (consistent with hold-up problems), but their interaction increases lending share by 23.4%—effects about 20 times larger than direct disaster impacts. Third, we characterize a market failure where competitive equilibrium systematically under-allocates credit to disaster regions, and demonstrate that public assistance partially corrects this inefficiency.

Our empirical analysis yields three key findings. *First*, disasters induce substantial credit reallocation. A one-standard-deviation increase in disaster-related property damage is associated with a 1.3% increase in lending share and a 11.6% increase in loan spreads for firms in affected counties (relative to sample means). At the same time, banks pull back in regions not hit by the disaster: lending in unaffected but financially connected counties declines by about 1.7%. These spillover effects indicate that banks reallocate capital from unaffected areas to meet surging credit demand in disaster zones.

Second, triadic network coordination has a dominant effect on credit allocation under stress. When borrower–lead–participant relationships are strong, lenders dramatically expand credit to disaster-hit firms: a one-standard-deviation increase in our triadic relationship measure increases a lender's syndication share by roughly 23.4%, and loan interest spreads decrease by about 6 basis points. This effect is an order of magnitude larger than the direct impact of the disaster shock itself, highlighting that the configuration of lending relationships largely determines which firms maintain credit access during a crisis.

Third, competitive lending markets under-provide credit to disaster-stricken regions, but public intervention helps correct this inefficiency. Banks internalize heightened default risk in disaster areas, ignoring the broader social value of restoring productive capacity. Consistent with our theoretical framework, we find a persistent credit shortfall in disaster regions. However, greater government aid substantially mitigates this gap: moving from the 10^{th} to 90^{th} percentile of FEMA relief reduces the credit under-supply by about 24%, though roughly 76% of the gap remains. In other words, public disaster assistance "crowds in" private lending rather than displacing it.

These findings contribute to several strands of literature. *First*, our theoretical framework extends the relationship lending literature beyond bilateral ties to multi-party coordination. While classical models examine bilateral bank-firm relationships (Petersen and Rajan, 1995; Boot and Thakor, 1994), syndicated lending requires coordination among three parties under asymmetric information. We provide formal microfoundations demonstrating why relationship capital operates as a network asset requiring triadic coordination, reconciling contradictory findings in prior syndicate literature where some studies find positive relationship effects (Bharath et al., 2011) while others document negative effects (Sufi, 2007) when examining bilateral dimensions in isolation.

Second, while prior studies document that banks shift credit in response to disasters (e.g., Koetter et al., 2020; Brown et al., 2021; Ivanov et al., 2022), we identify the specific mechanism behind this reallocation. Unlike Ivanov et al. (2022) and Koetter et al. (2020), who establish *that* credit shifts occur, we explain *how* multi-bank networks coordinate to redistribute capital—through triadic relationship strength. Whereas Brown et al. (2021) find that firms draw on credit lines (at higher rates) after severe weather shocks, our results reveal the network structures that enable or constrain such emergency lending. Our contribution is identifying the coordination mechanism: bilateral relationships create informational holdups unless complemented by the third-party connection that enables credible signaling.

Third, we add micro-level evidence to the disaster recovery literature. Our results illustrate the "build back better" mechanism at work in credit markets, complementing the macro-level findings of Tran and Wilson (2025). In particular, we show that robust lending networks—where banks and firms have dense interconnections—facilitate the efficient allocation of reconstruction capital. Moreover, our welfare analysis demonstrates that competitive credit markets systematically under-allocate resources to disaster regions even when functioning smoothly, providing theoretical foundations for why public aid can partially alleviate the residual credit shortfall. This characterizes a market failure distinct from standard market breakdowns: the risk premium wedge between competitive and social allocations justifies public intervention beyond humanitarian considerations.

Finally, our analysis has clear policy implications. Financial resilience to climate-related shocks depends not only on bank capitalization, but also on the structure of bank–firm networks. Policies that encourage the formation and preservation of multi-party lending relationships (for example, through credit guarantees or targeted capital relief for disaster lending) could strengthen the ability of the financial system to absorb localized shocks. However, our findings suggest that policies encouraging any single bilateral relationship dimension may be ineffective or even counterproductive. Instead, effective policies must support relationship formation across all three parties simultaneously—for instance, through information sharing platforms that reduce moral hazard while building reputation capital.

Our evidence also indicates that government disaster relief generates positive externalities by crowding in private credit. The sizable reduction in credit shortfalls associated with higher FEMA aid—24% from the 10^{th} to 90^{th} percentile—underscores that public funds complement, rather than substitute for, bank lending in crisis times. This crowding-in effect validates the efficiency-enhancing role of public assistance predicted by our theoretical framework: FEMA aid reduces risk premia that prevent efficient capital allocation in competitive equilibrium, thereby narrowing the gap between private and social optimum.

Furthermore, the asymmetric spillovers we document—where credit tightens in distant regions when disasters strike elsewhere—suggest that regulators and risk managers should account for indirect contagion through lending networks when assessing systemic climate-related risks. Our finding that triadic coordination effects are roughly 20 times larger than direct disaster impacts implies that regions with dense syndicated lending networks will exhibit substantially greater resilience to climate shocks. This creates potential for geographically concentrated vulnerability as network effects amplify regional disparities, requiring comprehensive climate risk assessment that extends beyond direct geographic exposure to incorporate network propagation channels.

As climate change intensifies disaster frequency and severity, understanding the institutional mechanisms that sustain credit flows when information asymmetries amplify becomes increasingly critical for financial stability policy. Our theoretical framework and empirical evidence demonstrate that these mechanisms operate through complex multi-party coordination requiring simultaneous strength across all bilateral relationships—an insight extending beyond disaster contexts to any environment where information frictions intensify, including financial crises, regulatory shocks, or technological disruptions.

Declarations

Funding

We have not received any financial assistance from any agency.

Availability of data and materials

We confirm that all pertinent information is either publicly or commercially available for further use.

Competing interests

No competing interests.

CRediT authorship contribution statement

S. M. Woahid Murad: Conceptualization, Methodology, Software, Data curation, Investigation, Formal Analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Robert B. Durand**: Conceptualization, Writing – review & editing, Supervision. **Chen Zheng**: Conceptualization, Writing – review & editing, Supervision.

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Tables

Table 1: Summary statistics of the variables

Variable	Definition	N	Mean	SD
Lending share	Lending share of firm i in syndicated loans arranged by bank j in county k.	159,411	16.387	29.087
Interest Rate	Margin BPS, the interest rate charged above the base rate, used as a proxy for interest rate.	141,363	162.7	212.1
Property exposure	Property damage (in constant million US$) in a natural disaster–affected county, multiplied by the lending share of bank j in that county. Normalized by bank j's total lending.	159,411	0.002	0.680
Log of Lenders Number	Natural logarithm of the number of lenders involved in the loan.	159,411	2.137	0.894
Log of Tenor Maturity	Natural logarithm of the number of months between the tranche activation and maturity dates.	151,811	3.593	0.682
Secured	Dummy variable equal to 1 if the tranche is secured.	159,411	0.334	0.466
Covenants	Dummy variable equal to 1 if financial covenants are present.	159,411	0.422	0.490
Participants–Lead Lender Relation	Average frequency of past syndications between participant lenders and the lead arranger in the last three years, normalized by the number of participants.	159,411	0.934	0.155
Borrower–Lead Lender Relation	Frequency of syndicated loans between borrower i and lead arranger j over the past three years, normalized by total borrowings of firm i.	159,411	0.083	0.168

Table 2: The effect of exposure to natural disasters on syndicated loans from the perspective of firm, bank, and county

	(1)	(2)	(3)
VARIABLES	All	All	Excluding Finance, Insurance and Real Estate
Property Exposure	0.303***	0.285***	0.282***
	(0.055)	(0.004)	(0.004)
Log of Lenders Number		3.308***	3.275***
		(0.125)	(0.141)
Log of Tenor Maturity		0.768***	0.810***
		(0.115)	(0.128)
Secured		2.194***	2.173***
		(0.199)	(0.216)
Covenants		0.926***	0.937***
		(0.165)	(0.184)
Constant	16.384***	5.468***	5.545***
	(0.000)	(0.443)	(0.500)
Firm FE	YES	YES	YES
Bank FE	YES	YES	YES
County FE	YES	YES	YES
Firm-Bank-County FE	YES	YES	YES
Industry FE	YES	YES	YES
Year-month FE	YES	YES	YES
Mean of the Dep. Var.	16.385	16.596	16.853
SD of Property Exposure	0.681	0.695	0.767
N	159,229	149,020	122,460
R-sq	0.780	0.784	0.783
Adj R-sq	0.617	0.623	0.617

Notes: This table reports the effect of property exposure to natural disasters on syndicated loan issuance. The sample consists of 159,411 firm-bank-county observations from April 1982 to December 2021. Firms in the public administration sector (SIC codes 9111–9999) are excluded. The dependent variable is the firm's lending share in the lead bank's total syndicated loan issuance. Column (1) includes property exposure as the primary explanatory variable, while Columns (2) and (3) introduce additional controls, including the log of the number of lenders, log of loan maturity, secured status, and covenants. Column (3) further excludes firms in the finance, insurance, and real estate sectors (SIC codes 6000–6799). All regressions incorporate firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3: The Impact of Natural Disaster Exposure on Syndicated Loans Excluding the Effects of Hurricane Katrina

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Excluded Katrina Affected Counties			Excluded All Counties		
	6 months after Katrina	12 months after Katrina	24 months after Katrina	6 months after Katrina	12 months after Katrina	24 months after Katrina
Property Exposure	0.285***	0.285***	0.285***	0.285***	0.286***	0.289***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Log of Lenders Number	3.310***	3.310***	3.311***	3.358***	3.377***	3.406***
	(0.125)	(0.125)	(0.125)	(0.128)	(0.131)	(0.138)
Log of Tenor Maturity	0.770***	0.772***	0.774***	0.807***	0.817***	0.815***
	(0.115)	(0.115)	(0.115)	(0.118)	(0.120)	(0.126)
Secured	2.194***	2.193***	2.187***	2.173***	2.227***	2.224***
	(0.199)	(0.199)	(0.199)	(0.203)	(0.208)	(0.221)
Covenants	0.922***	0.922***	0.923***	0.941***	0.946***	1.049***
	(0.165)	(0.165)	(0.165)	(0.169)	(0.173)	(0.183)
Constant	5.457***	5.451***	5.441***	5.332***	5.413***	5.667***
	(0.443)	(0.443)	(0.443)	(0.453)	(0.463)	(0.484)
Firm FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Firm-Bank-County FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
N	148973	148946	148898	143575	137581	127537
R-sq	0.784	0.784	0.784	0.785	0.786	0.787
Adj R-sq	0.623	0.623	0.623	0.620	0.619	0.614

Notes: This table reports the impact of exposure to natural disasters on syndicated loan issuance, excluding the effects of Hurricane Katrina. From columns (1) to (3), we exclude only Katrina affected counties for 6 months (in column 1), 12 months (in column 2) and 24 months (in column 3) after Katrina. Likewise, we exclude all counties for 6 months (in column 4), 12 months (in column 5) and 24 months (in column 6) after Katrina in column (4) to (6). The full sample consists of 159,411 firm-bank-county observations from April 1982 to December 2021. Firms in the public administration sector (SIC codes 9111–9999) are excluded. The dependent variable is the firm's lending share in the lead bank's total syndicated loan issuance. Property exposure is the primary explanatory variable, with additional controls including the log of the number of lenders, log of loan maturity, secured status, and covenants. All regressions incorporate firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Effects of Natural Disaster Exposure on Syndicated Loan Spillover in Neighbouring Counties

	(1)	(2)
VARIABLES	Exposure from the sum of neighbours' property damage	Exposure from the mean of neighbours' property damage
	Lending Share	Lending Share
Property Exposure	0.989***	0.254***
	(0.053)	(0.004)
Log of Lenders Number	3.307***	3.308***
	(0.125)	(0.125)
Log of Tenor Maturity	0.768***	0.768***
	(0.115)	(0.115)
Secured	2.194***	2.194***
	(0.199)	(0.199)
Covenants	0.927***	0.927***
	(0.165)	(0.165)
Constant	5.467***	5.467***
	(0.443)	(0.443)
Firm FE	YES	YES
Bank FE	YES	YES
County FE	YES	YES
Firm-Bank-County FE	YES	YES
Industry FE	YES	YES
Year-month FE	YES	YES
N	149020	149020
R-sq	0.784	0.784
Adj R-sq	0.623	0.623

Notes: This table reports the effect of property exposure to natural disasters on syndicated loan issuance. The sample consists of 159,411 firm-bank-county observations from April 1982 to December 2021. Firms in the public administration sector (SIC codes 9111–9999) are excluded. The dependent variable is the firm's lending share in the lead bank's total syndicated loan issuance. Column (1) takes aggregate property damage of adjacent counties to construct property exposure, while Column (2) considers the average value of property damage of adjacent counties. Columns (1) and (2) include property exposure as the primary explanatory variable. Additional controls are the log of the number of lenders, log of loan maturity, secured status, and covenants. All regressions incorporate firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: 2SLS Regression Results: Jackknife and Lewbel Instrumental Variables

	Jackknife IV		Lewbel IV	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	Property Exposure	Lending Share	Property Exposure	Lending Share
Property Exposure		0.1825***		0.2777***
		(0.0629)		(0.0068)
Log of Lenders Number	-59.772***	3.3071***	-0.0015***	3.3076***
	(14.263)	(0.1196)	(0.0002)	(0.1249)
Log of Tenor Maturity	4.110***	0.7681***	0.0001	0.7681***
	(0.980)	(0.1102)	(0.0002)	(0.1151)
Secured	-100.408***	2.1935***	-0.0013***	2.1943***
	(23.957)	(0.1908)	(0.0003)	(0.1992)
Covenants	-77.412***	0.9258***	-0.0007***	0.9264***
	(18.470)	(0.1576)	(0.0003)	(0.1646)
Jackknife IV – FEMA MA	-11,857***			
	(2,829)			
Lewbel IV – Log of Lenders Number			-0.9351***	
			(0.0528)	
Lewbel IV – Log of Tenor Maturity			0.8151***	
			(0.0664)	
Lewbel IV – Covenant			0.7531***	
			(0.0432)	
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Firm-Bank-County FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	149,020	149,020	149,020	149,020
Diagnostic Tests				
F test of excluded instruments	17.56***		>999***	
Overidentification test (Hansen J)		–		3.561
				[0.168]

Notes: This table reports two-stage least squares estimates of syndicated loan issuance using both the Jackknife Instrumental Variables Estimator (JIVE2) and Lewbel's heteroskedasticity-based instruments. Columns (1) and (2) correspond to the Jackknife IV first- and second-stage regressions, while Columns (3) and (4) report results from the Lewbel IV estimation. The Jackknife instrument is constructed using a 10-year moving average of FEMA disaster declarations to mitigate finite-sample bias (Angrist et al., 1999), and JIVE2 applies a constant correction based on the effective sample size to mitigate cluster-level bias in first-stage fitted values. Lewbel (2012) IV instruments are generated by interacting mean-centered exogenous covariates with heteroskedasticity-derived residuals from the first-stage regression, providing valid identification when the covariance restriction $\text{cov}(Z, \varepsilon_1\varepsilon_2) = 0$ holds. The Hansen J-statistic tests overidentifying restrictions in the Lewbel specification; p-values are reported in brackets. All specifications include firm, bank, county, firm–bank–county, industry, and year–month fixed effects. Standard errors are clustered at the firm–bank–county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: The effect of exposure to natural disasters on interest rates

	(1)	(2)	(3)
VARIABLES	All	All	Excluding Finance, Insurance and Real Estate
Property Exposure	0.139***	0.192***	0.184***
	(0.031)	(0.025)	(0.027)
Log of Lenders Number		-13.674***	-13.323***
		(2.336)	(2.778)
Log of Tenor Maturity		0.492	0.326
		(0.774)	(0.928)
Secured		39.584***	40.991***
		(1.160)	(1.277)
Covenants		-7.320***	-8.249***
		(1.193)	(1.517)
Constant	161.015***	178.026***	182.965***
	(0.000)	(4.426)	(4.855)
Firm FE	YES	YES	YES
Bank FE	YES	YES	YES
County FE	YES	YES	YES
Firm-Bank-County FE	YES	YES	YES
Industry FE	YES	YES	YES
Year-month FE	YES	YES	YES
N	136,047	130,621	107,766
R-sq	0.606	0.604	0.585
Adj R-sq	0.304	0.298	0.259

Notes: This table reports the effect of property exposure to natural disasters on interest rates. The sample consists of 159,411 firm-bank-county observations from April 1982 to December 2021. Firms in the public administration sector (SIC codes 9111–9999) are excluded. The dependent variable is the interest rates. Similar to Table 2, Column (1) includes property exposure as the primary explanatory variable, while Columns (2) and (3) introduce additional controls, including the log of the number of lenders, log of loan maturity, secured status, and covenants. Column (3) further excludes firms in the finance, insurance, and real estate sectors (SIC codes 6000–6799). All regressions incorporate firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Effect of exposure to natural disasters on syndicated loans and interest rates in connected markets

	(1)	(2)	(3)	(4)
VARIABLES	All		Excluding Finance, Insurance, and Real Estate	
	Lending Share	Interest Rate	Lending Share	Interest Rate
Bank's Property Exposure	-0.487***	0.094	-0.451***	0.019
	(0.135)	(0.371)	(0.131)	(0.382)
Log of Lenders Number	3.325***	-13.371***	3.312***	-13.183***
	(0.130)	(2.479)	(0.147)	(2.957)
Log of Tenor Maturity	0.808***	0.227	0.838***	0.155
	(0.120)	(0.771)	(0.134)	(0.922)
Secured	2.178***	40.568***	2.130***	42.021***
	(0.208)	(1.201)	(0.226)	(1.324)
Covenants	0.835***	-7.548***	0.826***	-8.601***
	(0.171)	(1.265)	(0.192)	(1.654)
Constant	5.202***	177.776***	5.299***	182.745***
	(0.462)	(4.856)	(0.523)	(5.352)
Firm FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Firm-Bank-County FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
N	138,251	120,868	113,553	99,700
R-sq	0.783	0.595	0.781	0.576
Adj R-sq	0.617	0.273	0.610	0.233

Notes: This table reports the effect of property exposure to natural disasters on syndicated lending and interest rates in the unaffected counties. We further restrict the sample to banks that actively lend to disaster-affected counties during the study period, ensuring that observed spillovers reflect the behavior of connected lenders with overlapping exposure networks. The sample consists of 151,048 firm-bank-county observations from April 1982 to December 2021. Firms in the public administration sector (SIC codes 9111–9999) are excluded. We also exclude the counties for the time when they experience FEMA-declared disasters. Columns (1) and (2) include all industries, while Columns (3) and (4) exclude the finance, insurance, and real estate sectors (SIC codes 6000–6799). The dependent variables are lending share and interest rate. Property exposure is the primary explanatory variable, with additional controls including the log of the number of lenders, log of loan maturity, secured status, and covenants. Standard errors are clustered at firm-bank-county level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Lending Relationship, Loan Issuance and Interest Rate

	Continuous Measures		Categorical Measures	
	(1)	(2)	(3)	(4)
VARIABLES	Lending Share	Interest Rate	Lending Share	Interest Rate
Property Exposure	0.297***	0.271***	0.285***	0.209***
	(0.004)	(0.030)	(0.004)	(0.026)
Borrower–Lead Lender Relation	–23.652***	75.339***		
	(4.156)	(26.062)		
Participants–Lead Lender Relation	–15.434***	–39.935***		
	(0.826)	(5.637)		
Borrower–Lead × Participants–Lead Relation	24.995***	–77.957***		
	(4.233)	(26.859)		
Network Type (base = both relationships low):				
Only Participants–Lead High			3.963***	–11.521***
			(0.497)	(2.644)
Only Borrower–Lead High			–0.368***	–3.637***
			(0.123)	(0.568)
Both High (Triadic)			4.721***	–12.945***
			(0.662)	(3.629)
Log of Lenders Number	2.837***	–15.496***	3.324***	–13.435***
	(0.125)	(2.231)	(0.125)	(2.343)
Log of Tenor Maturity	0.755***	0.451	0.729***	0.353
	(0.114)	(0.774)	(0.115)	(0.778)
Secured	2.019***	39.048***	2.189***	39.579***
	(0.198)	(1.148)	(0.199)	(1.160)
Covenants	1.009***	–7.089***	0.900***	–7.499***
	(0.164)	(1.180)	(0.165)	(1.201)
Constant	20.943***	219.568***	5.654***	179.754***
	(0.912)	(4.440)	(0.447)	(4.381)
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Firm-Bank-County FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	149,020	130,621	149,020	130,621
R-squared	0.786	0.605	0.785	0.604
Adj. R-squared	0.626	0.299	0.623	0.298

Notes: This table reports the effect of previous borrowing and lending relationships on syndicated loan issuance and interest rate spreads. The sample consists of 159,411 firm-bank-county observations from April 1982 to December 2021. Firms in the public administration sector (SIC codes 9111–9999) are excluded. The dependent variables are the firm's lending share in the lead bank's total syndicated loan issuance (columns 1 and 3) and Interest Rate (loan spreads in basis points) (columns 2 and 4). Columns (1)–(2) use continuous relationship measures. *Borrower–Lead Lender Relation* measures the frequency of syndicated loan issuance between firm i and lead lender j over the past 3 years, normalized by the total number of syndicated loans received by firm i during the same period. *Participants–Lead Lender Relation* captures the average number of times the participating lenders in the current syndicate have previously partnered with lead lender j in the past 3 years, normalized by the number of participant lenders in the current loan syndicate. Columns (3)–(4) use categorical measures constructed by splitting both relationship variables at their sample medians: *Only Participants–Lead High* indicates the participant–lead relationship exceeds the median while the borrower–lead relationship does not; *Only Borrower–Lead High* indicates the borrower–lead relationship exceeds the median while the participant–lead relationship does not; *Both High (Triadic)* indicates both relationships exceed their respective medians. The baseline category (omitted) is both relationships below their medians. All specifications control for the log of the number of lenders, log of loan maturity, secured status, and covenants, and include firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at the firm-bank-county level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Effect of Exposure to Fire, Flood, and Hurricane Disasters on Syndicated Loan

	(1)	(2)	(3)	(4)
VARIABLES	Lending Share	Lending Share	Lending Share	Lending Share
Property Exposure × Fire	17.648**			17.644**
	(8.683)			(8.681)
Property Exposure × Flood		323.543***		323.541***
		(97.192)		(97.183)
Property Exposure × Hurricane			0.283***	0.283***
			(0.004)	(0.004)
Log of Lenders Number	3.306***	3.306***	3.308***	3.307***
	(0.125)	(0.125)	(0.125)	(0.125)
Log of Tenor Maturity	0.768***	0.771***	0.768***	0.771***
	(0.115)	(0.115)	(0.115)	(0.115)
Secured	2.190***	2.198***	2.194***	2.198***
	(0.199)	(0.199)	(0.199)	(0.199)
Covenants	0.925***	0.923***	0.926***	0.925***
	(0.165)	(0.165)	(0.165)	(0.165)
Constant	5.472***	5.462***	5.468***	5.457***
	(0.443)	(0.443)	(0.443)	(0.443)
Firm FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Firm–Bank–County FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year–Month FE	YES	YES	YES	YES
N	149,020	149,020	149,020	149,020
R-sq	0.784	0.784	0.784	0.784
Adj R-sq	0.622	0.623	0.623	0.623

Notes: This table reports the effect of property exposure to major natural disaster types—fire, flood, and hurricane—on syndicated loan issuance. The sample consists of 159,411 firm–bank–county observations from April 1982 to December 2021, excluding firms in the public administration sector (SIC codes 9111–9999). The dependent variable is the firm's lending share in the lead bank's total syndicated loan issuance. Interaction terms are constructed by multiplying property exposure with an indicator for each disaster type (equals 1 if the disaster is of that type, 0 otherwise). "Hurricane" includes Coastal Storm, Hurricane, Severe Ice Storm, Severe Storm, Snowstorm, and Tornado; "Flood" includes Dam/Levee Break and Flood. Columns (1)–(3) report results for individual disaster types, while Column (4) combines all three. All regressions include firm, bank, county, firm–bank–county, industry, and year–month fixed effects, as well as controls for the log number of lenders, log loan maturity, secured status, and covenants. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Effect of Exposure to Natural Disasters on Syndicated Loans in Disaster-Prone and Non-Disaster-Prone Counties

	(1)	(2)
	Disaster-Prone Counties	Non-Disaster-Prone Counties
VARIABLES	Lending Share	Lending Share
Property Exposure	0.280***	28.305*
	(0.013)	(15.716)
Log of Lenders Number	3.149***	3.293***
	(0.386)	(0.133)
Log of Tenor Maturity	1.001***	0.764***
	(0.371)	(0.122)
Secured	1.372**	2.224***
	(0.595)	(0.213)
Covenants	0.277	1.026***
	(0.568)	(0.174)
Constant	3.684**	5.653***
	(1.451)	(0.469)
Firm FE	YES	YES
Bank FE	YES	YES
Industry FE	YES	YES
County FE	YES	YES
Firm-Bank-County FE	YES	YES
Year-month FE	YES	YES
N	13,738	135,270
R-sq	0.799	0.785
Adj R-sq	0.614	0.623

Notes: This table reports the effect of property exposure to natural disasters on syndicated loan issuance, comparing disaster-prone counties with non-disaster-prone counties. Disaster-prone counties are defined as the 14 U.S. counties that account for approximately 50% of total disaster-related property damage during the sample period (April 1982 to December 2021), located in California, Florida, Louisiana, Mississippi, New Jersey, and Texas. All other counties are classified as non-disaster-prone. The dependent variable is the firm's lending share in the lead bank's total syndicated loan issuance. Both columns include property exposure as the primary explanatory variable, along with additional controls such as the log of the number of lenders, log of loan maturity, secured status, and covenants. All regressions incorporate firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11: The effect of exposure to natural disasters across different loan and firm sizes

	(1)	(2)	(3)	(4)
VARIABLES	Smaller loan	Larger loan	Smaller firm	larger firm
Property Exposure	4.631***	0.220***	254.951***	0.286***
	(1.698)	(0.018)	(85.640)	(0.004)
Log of Lenders Number	0.365***	3.457***	2.436***	3.462***
	(0.009)	(0.369)	(0.261)	(0.148)
Log of Tenor Maturity	0.148***	0.693**	-0.064	1.090***
	(0.008)	(0.344)	(0.238)	(0.137)
Secured	0.149***	2.931***	0.479	2.707***
	(0.015)	(0.538)	(0.379)	(0.251)
Covenants	0.146***	1.333***	0.410	0.827***
	(0.013)	(0.481)	(0.334)	(0.202)
Constant	-0.166***	28.225***	10.634***	3.845***
	(0.032)	(1.468)	(0.871)	(0.537)
Firm FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Firm-Bank-County FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
N	74,781	51,666	37,137	104,487
R-sq	0.601	0.736	0.808	0.783
Adj R-sq	0.242	0.425	0.588	0.627

Notes: This table examines the effect of property exposure to natural disasters on syndicated loan issuance across different loan and firm sizes. The sample comprises 159,411 firm-bank-county observations from April 1982 to December 2021, excluding firms in the public administration sector (SIC codes 9111–9999). The dependent variable is the firm's lending share in the lead bank's total syndicated loan issuance. Columns (1) and (2) classify loans based on size, with Column (1) representing smaller loans (less than or equal to the median loan size) and Column (2) representing larger loans (greater than the median loan size). Similarly, Columns (3) and (4) categorize firms based on annual sales in real terms, where Column (3) includes smaller firms (annual sales less than or equal to the median) and Column (4) includes larger firms (annual sales greater than the median). All regressions include property exposure as the primary explanatory variable and control for the log of the number of lenders, log of loan maturity, secured status, and covenants. Fixed effects for firm, bank, county, firm-bank-county, industry, and year-month are incorporated. Standard errors, clustered at firm-bank-county level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Placebo test of the baseline regressions

	(1)	(2)	(3)	(4)
VARIABLES	All	All	Excluding Finance, Insurance and Real Estate	Excluding Finance, Insurance and Real Estate
	Lending Share	Interest Rate	Lending Share	Interest Rate
$\widetilde{\text{Property}}$ Exposure	0.0386	0.0656	0.0554	-0.1542
	(0.0117)	(0.0156)	(0.0125)	(0.0154)
Loan Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table presents the results of the placebo test, conducted by randomly drawing property exposure values from its sample distribution. The reported coefficients represent the average estimate based on 1,000 iterations of randomly generated samples. The sample comprises 159,411 firm-bank-county observations from April 1982 to December 2021, excluding firms in the public administration sector (SIC codes 9111–9999). The dependent variables are lending share and interest rates. Columns (1) and (2) include the full sample, while Columns (3) and (4) exclude firms in the finance, insurance, and real estate sectors (SIC codes 6000–6799). Both columns control for the log of the number of lenders, log of loan maturity, secured status, and covenants. All regressions incorporate firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors, clustered at firm-bank-county level, are reported in parentheses. None of the estimates are significant even at the 10% significance level.

Figures

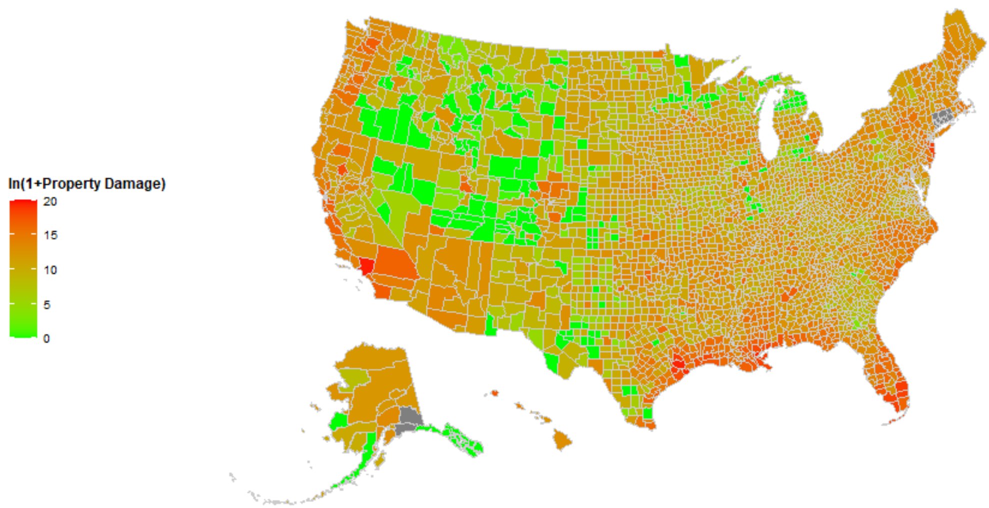


Figure 1: **FEMA declared property damage due to natural disaster from 1982:M4 to 2021:M12.** The figure illustrates the spatial distribution of total property damage from FEMA-declared natural disasters across U.S. counties from April 1982 to December 2021. The color gradient represents the natural logarithm of property damage plus one, with darker shades indicating higher levels of cumulative damage. Disaster exposure is geographically concentrated, particularly in coastal and southern regions.

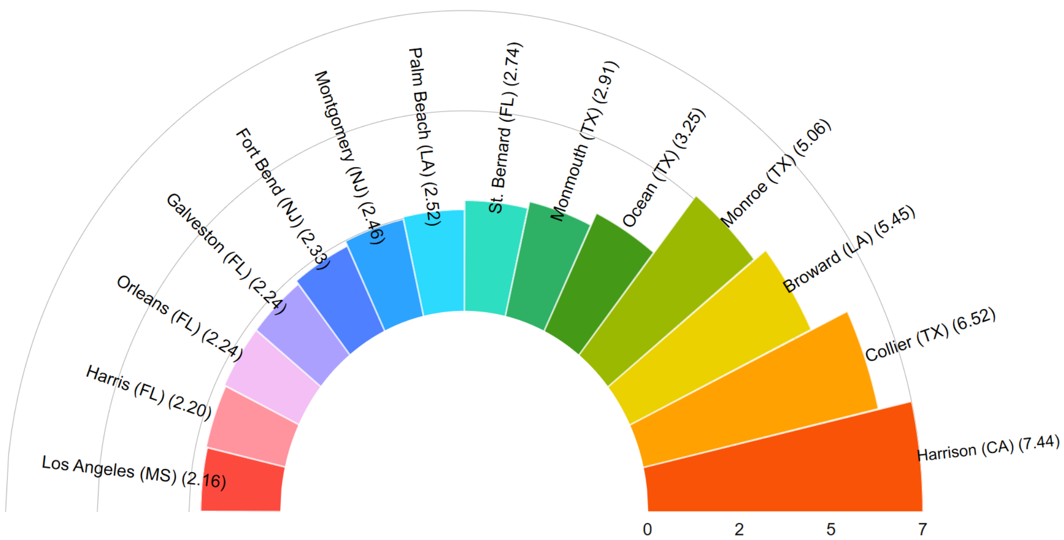


Figure 2: **Major natural disaster affected counties.** The figure displays the top counties by share of total property damage from natural disasters, expressed as a percentage of national damage. County names are followed by their respective shares in percentage. Nearly 50% of all disaster-related property damage is concentrated in just 12 counties, indicating substantial geographic concentration of disaster exposure.

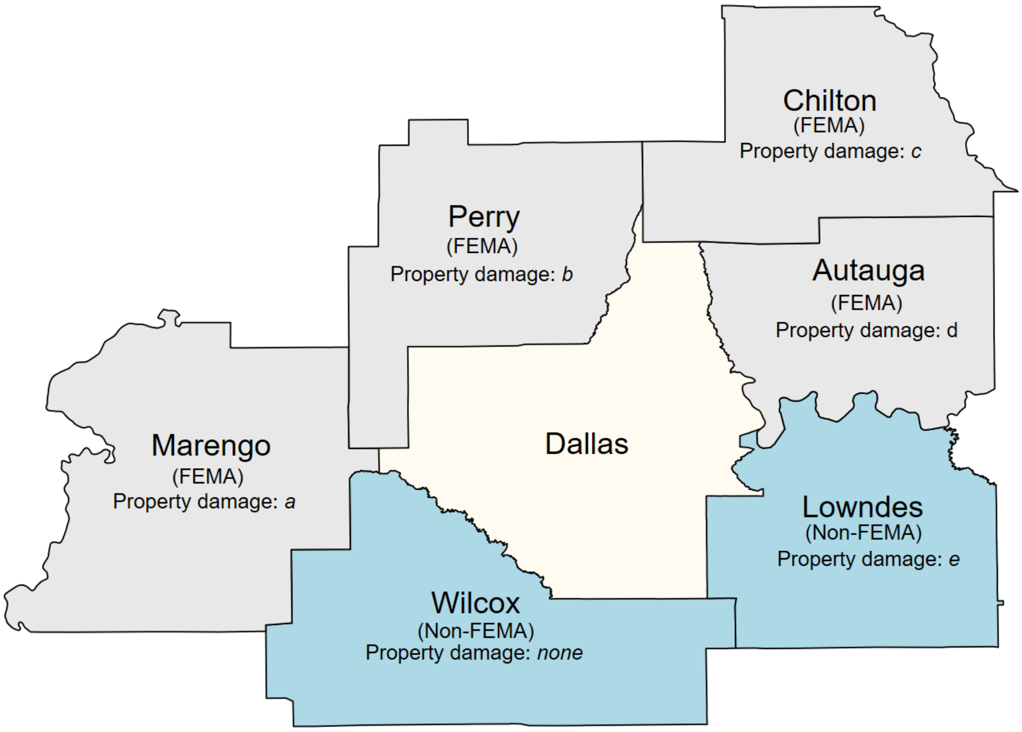


Figure 3: **Mapping neighbouring counties.** The figure illustrates how we define neighboring counties to estimate spillover effects from disaster exposure. Dallas County (center) is surrounded by six adjacent counties. Of these, for example, five experienced FEMA-declared disasters during a particular time t. The shaded counties show variation in both FEMA declaration status and property damage levels. For spillover analysis, we construct two exposure measures—sum and mean—based on the property damage in FEMA-declared neighboring counties only. For example, the total spillover exposure to Dallas County is calculated using property damage values $a + b + c + d$, excluding damage in non-FEMA counties like Lowndes. See Equations (6a) and (6b) for formal definitions.

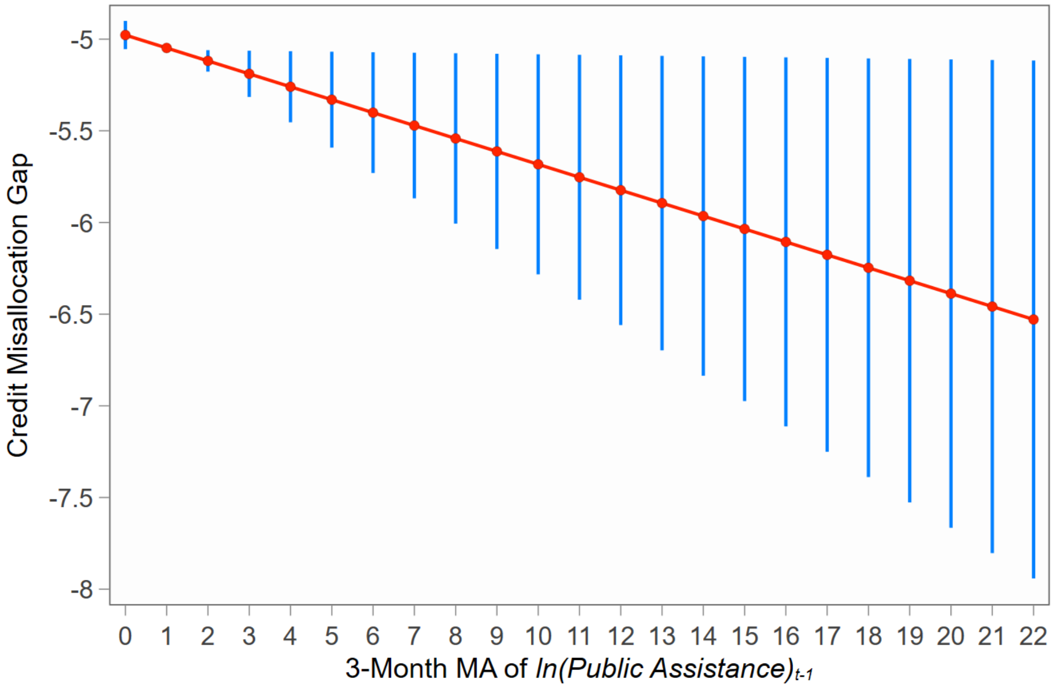
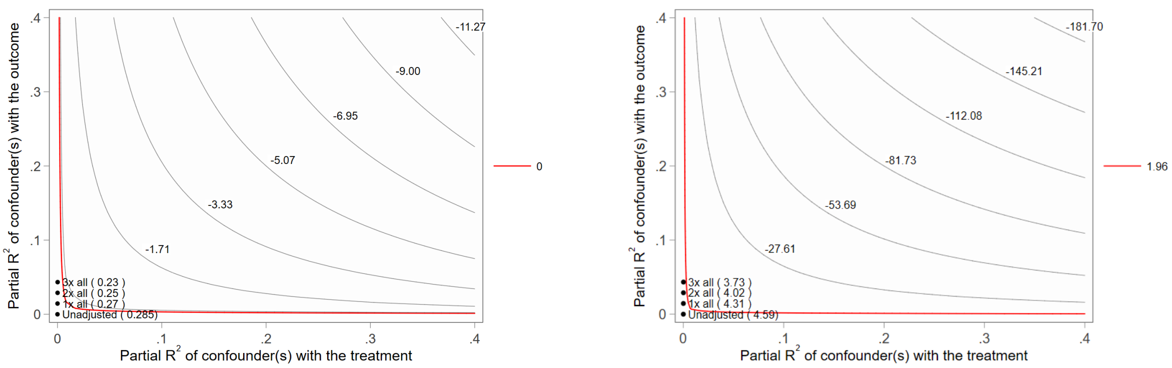


Figure 4: **FEMA Public Assistance and Risk-Adjusted Credit Misallocation.** The figure depicts the marginal effect of exogenous public assistance on the credit misallocation gap. The horizontal axis shows the 3-month moving average of log-transformed FEMA public assistance at the county level, lagged by one month. The vertical axis depicts the predicted reduction in the credit misallocation gap. The gap is defined as the difference between expected allocations, proxied by the log of county-level property damage and the log of realized syndicated loan allocations during FEMA-declared disaster periods. Margins are estimated including the log of the number of lenders, log of loan maturity, secured status, covenants and the fixed effects of firm, bank, county, firm-bank-county, industry, and year-month fixed effects. Standard errors are clustered at firm-bank-county level. Error bars indicate 95% confidence intervals via the Delta-method. The figure supports the *risk-adjusted misallocation gap* postulated in Hypothesis 6. The figure indicates that higher levels of public assistance systematically reduce misallocation following disaster shocks.



(a) Sensitivity contour plots of point estimates

(b) Sensitivity contour plots of t-values

Figure 5: **Sensitivity Analysis of *Property Exposure*.** Panel 5a shows how the estimated coefficients on *Property Exposure* change when hypothetically including confounders that are one to three times stronger than the included loan characteristics (log of the number of lenders, log of loan maturity, secured status, and covenants) after controlling the fixed effects. Panel 5b presents the corresponding t-values under the same hypothetical confounders.

Appendix A. Additional Figure

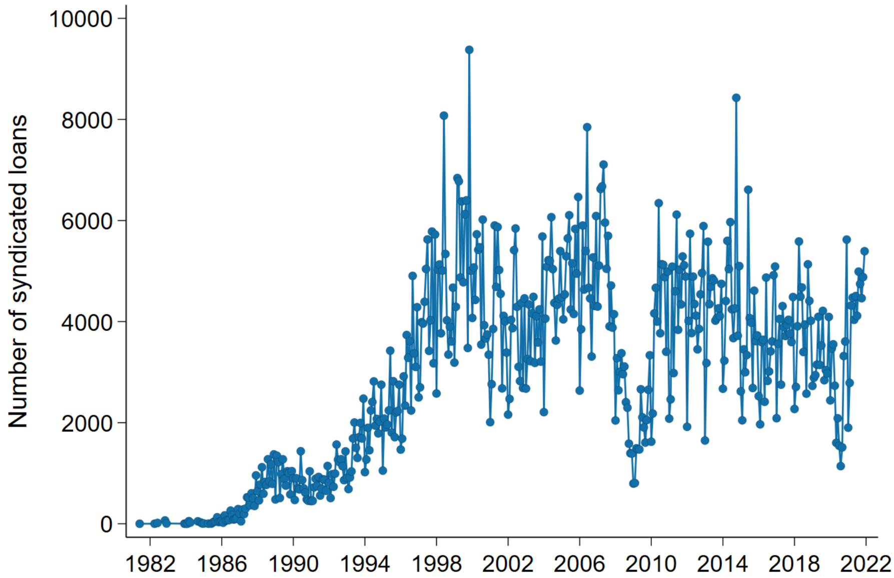


Figure A.1: **Number of syndicated loans issued to the US firms** Number of syndicated loans issued to U.S. firms, 1982–2021. The figure shows the monthly count of syndicated loan deals where the borrower is a US-based firm. The data reveal strong growth through the 1990s and early 2000s, followed by cyclical fluctuations and a noticeable decline during the global financial crisis.

Appendix B. Theoretical Model

This appendix develops a formal model of credit allocation in syndicated loan markets following natural disasters. The model microfounds the hypotheses tested in Section 2 and provides theoretical grounding for the triadic coordination mechanism documented empirically. We characterize competitive equilibrium in syndicated lending with disaster shocks, demonstrate Pareto inefficiency arising from incomplete risk markets, and derive conditions under which public assistance improves welfare.

B.1. Model Environment

B.1.1. Economic Geography and Production

Consider an economy with a continuum of counties indexed by $k \in [0, 1]$. Each county k hosts firms that produce output using capital K_k and labor L_k through Cobb-Douglas technology:

$$Y_k = A_k K_k^{\beta} L_k^{1-\beta} \tag{B1}$$

where A_k is county-level total factor productivity and $\beta \in (0, 1)$ is capital's share. Normalize labor supply to unity ($L_k = 1$) in each county, so $Y_k = A_k K_k^{\beta}$ and the marginal product of capital is:

$$MPK_k = \frac{\partial Y_k}{\partial K_k} = \beta A_k K_k^{\beta-1} \tag{B2}$$

At time $t = 0$, a natural disaster of intensity $\delta_k \in [0, \bar{\delta}]$ strikes county k, destroying fraction δ_k of the initial capital stock $\bar{K}_k$. Post-disaster capital becomes:

$$K_k = (1 - \delta_k)\bar{K}_k + I_k \tag{B3}$$

where I_k denotes new investment financed through syndicated loans. Capital destruction raises marginal product through diminishing returns:

$$\frac{\partial MPK_k}{\partial \delta_k} = -\beta(\beta - 1)A_k[(1 - \delta_k)\bar{K}_k]^{\beta-2} \cdot (-\bar{K}_k) > 0 \tag{B4}$$

This is the *productivity channel*: disasters elevate returns to capital investment in affected counties, creating demand for external financing.

B.1.2. Syndicated Lending Structure

Firm i in county k seeks investment I_i through a syndicated loan involving three parties:

1. **Borrower (Firm i):** Maximizes expected profit $\mathbb{E}[\pi_i] = MPK_k \cdot I_i - (1+r_i)I_i$, where r_i is the loan interest rate. The firm's optimal investment satisfies $MPK_k = 1 + r_i$.

2. **Lead Arranger (Bank j):** Screens and structures the loan, retaining share $\alpha_{ij} \in (0, 1)$ and syndicating $(1 - \alpha_{ij})I_i$ to participants. The lead incurs screening cost $c(e_{ij})$ where $e_{ij} \in [0, 1]$ denotes screening effort. Higher effort reduces default probability: $p_d(e_{ij}, \delta_k) = p_0 + \lambda\delta_k - \phi e_{ij}$ with $\lambda > 0$ (disasters increase risk) and $\phi > 0$ (screening reduces risk).

3. **Participants (Banks $p \in \mathcal{P}_{ij}$):** Collectively provide $(1 - \alpha_{ij})I_i$, each participant receiving share α_{pij} with $\sum_{p\in\mathcal{P}_{ij}} \alpha_{pij} = 1 - \alpha_{ij}$. Participants observe the lead's screening effort imperfectly.

The syndicated loan market differs fundamentally from bilateral lending because it requires coordination among all three parties under asymmetric information.

B.1.3. Information Structure and Relationship Capital

Information asymmetries operate along two dimensions:

Borrower-Lead Information Asymmetry: The lead arranger observes a private signal σ_i about firm quality after exerting screening effort e_{ij}. The signal's precision increases with both effort and relationship capital R^{BL}_{ij}:

$$\sigma_i \sim N(\theta_i, \sigma^2(e_{ij}, R^{BL}_{ij})) \quad \text{where} \quad \sigma^2(e, R^{BL}) = \frac{\sigma_0^2}{(1 + \gamma_1 R^{BL})(1 + \phi_1 e)} \tag{B5}$$

Here θ_i is the firm's true type (unobservable), $\gamma_1 > 0$ captures relationship benefits, and $\phi_1 > 0$ captures screening effectiveness. Strong borrower-lead relationships ($R_{ij}^{BL} \uparrow$) enable more precise information acquisition.

Lead-Participant Information Asymmetry: Participants cannot directly observe the lead's signal σ_i or screening effort e_{ij}. They observe only the lead's retained share α_{ij} and loan terms (I_i, r_i). However, strong participant-lead relationships R_j^{PL} enable credible signaling through reputation. Define the lead's reputation capital as:

$$\Omega_j(R_j^{PL}) = \omega_0 + \gamma_2 R_j^{PL} \tag{B6}$$

where $\gamma_2 > 0$ measures relationship strength and Ω_j determines the cost of deviating from truthful information sharing.

B.2. Equilibrium Characterization

B.2.1. Loan Pricing with Disaster Risk

The loan interest rate must compensate lenders for expected losses. In competitive equilibrium, the zero-profit condition for the syndicate is:

$$r_i = r_f + \rho_{ik}(e_{ij}, R_{ij}^{BL}, R_j^{PL}, \delta_k) \tag{B7}$$

where r_f is the risk-free rate and ρ_{ik} is the risk premium satisfying:

$$\rho_{ik} = \frac{p_d(e_{ij}, \delta_k) \cdot LGD_i}{1 - p_d(e_{ij}, \delta_k)} \tag{B8}$$

with LGD_i denoting loss-given-default.

Substituting the default probability $p_d = p_0 + \lambda\delta_k - \phi e_{ij}$ and approximating for small default rates:

$$\rho_{ik} \approx (p_0 + \lambda\delta_k - \phi e_{ij}) \cdot LGD_i \tag{B9}$$

The lead chooses screening effort e_{ij} to maximize net return on its retained share, trading off default reduction against screening costs. The first-order condition yields:

$$e_{ij}^* = \bar{e} + \eta R_{ij}^{BL} \tag{B10}$$

where $\eta > 0$ because stronger borrower-lead relationships increase the value of firm-specific information, justifying higher screening effort. Substituting optimal effort into (B9):

$$\rho_{ik} = \rho_0 + \lambda\delta_k - \gamma R_{ij}^{BL} \tag{B11}$$

where $\rho_0 \equiv (p_0 - \phi\bar{e})LGD_i$ is the baseline risk premium and $\gamma \equiv \phi\eta LGD_i$ captures the risk-reducing effect of borrower-lead relationships.

Empirical Prediction (Hypothesis 2): From equation (B11), $\partial r_i/\partial \delta_k = \lambda > 0$, implying loan spreads increase with disaster intensity. This generates Hypothesis 2.

B.2.2. Credit Allocation with Binding Constraints

Banks allocate their limited credit supply across counties by comparing risk-adjusted returns. Let s_{ijk} denote bank j's lending share to firm i in county k. The bank maximizes:

$$\max_{\{s_{ijk}\}} \sum_{i,k} s_{ijk} \left[r_i - \rho_{ik} - \frac{\kappa}{2} s_{ijk} \right] \tag{B12}$$

subject to $\sum_{i,k} s_{ijk} = 1$ (lending shares sum to unity) and $s_{ijk} \geq 0$.

The term $\frac{\kappa}{2} s_{ijk}$ captures convex lending costs from monitoring and capacity constraints. The first-order condition with Lagrange multiplier μ yields:

$$r_i - \rho_{ik} - \kappa s_{ijk} = \mu \quad \forall (i,k) \text{ with } s_{ijk} > 0 \tag{B13}$$

For two counties k and k' receiving positive lending:

$$MPK_k - \rho_k - \kappa s_k = MPK_{k'} - \rho_{k'} - \kappa s_{k'} \tag{B14}$$

where we suppress firm indices for clarity.

Banks equalize risk-adjusted marginal returns across regions. Differentiating with respect to disaster intensity δ_k using the implicit function theorem:

$$\frac{\partial s_k}{\partial \delta_k} = \frac{\frac{\partial MPK_k}{\partial \delta_k} - \frac{\partial \rho_k}{\partial \delta_k}}{-\frac{\partial MPK_k}{\partial s_k} - \frac{\partial MPK_{k'}}{\partial s_{k'}} - 2\kappa} \tag{B15}$$

The denominator is negative by diminishing returns and convex costs. The numerator has two competing terms:

- **Productivity effect:** $\frac{\partial MPK_k}{\partial \delta_k} > 0$ from equation (B4)
- **Risk effect:** $\frac{\partial \rho_k}{\partial \delta_k} = \lambda > 0$ from equation (B11)

If the productivity effect dominates ($\frac{\partial MPK_k}{\partial \delta_k} > \lambda$), then $\frac{\partial s_k}{\partial \delta_k} > 0$: banks increase lending shares to disaster-affected counties.

Proposition 1 (Credit Reallocation to Disaster Regions)**.** *When the marginal product increase from capital destruction exceeds the disaster-induced risk premium increase ($\frac{\partial MPK_k}{\partial \delta_k} > \lambda$), competitive banks reallocate credit toward disaster-affected counties:* $\frac{\partial s_k}{\partial \delta_k} > 0$.

Empirical Prediction (Hypothesis 1): Proposition 1 generates Hypothesis 1, predicting positive association between property damage exposure and lending share.

B.2.3. Spillover Effects from Binding Constraints

The binding constraint $\sum_{i,k} s_{ijk} = 1$ implies that increases in disaster-region lending require decreases elsewhere. Define bank j's disaster exposure as:

$$PExposure_j \equiv \sum_k \delta_k \cdot \left(\frac{L_{jk}}{\sum_{k'} L_{jk'}} \right) \tag{B16}$$

measuring the weighted average disaster intensity across the bank's portfolio.

For an unaffected county k' (where $\delta_{k'} = 0$), totally differentiating the constraint:

$$\sum_k \frac{\partial s_{jk}}{\partial PExposure_j} = 0 \tag{B17}$$

Since disaster-affected counties experience $\frac{\partial s_{jk}}{\partial PExposure_j} > 0$ (from Proposition 1), unaffected counties must have $\frac{\partial s_{jk'}}{\partial PExposure_j} < 0$ to satisfy the constraint.

Proposition 2 (Spillover Effects in Unaffected Markets)**.** *Banks with greater disaster exposure reduce lending shares in unaffected counties:* $\frac{\partial s_{jk'}}{\partial PExposure_j} < 0$ *for* $\delta_{k'} = 0$.

Empirical Prediction (Hypothesis 3): Proposition 2 generates Hypothesis 3.

The interest rate effect in spillover regions is ambiguous. From the zero-profit condition $r_{k'} = r_f + \rho_{k'}$, and noting that $\rho_{k'}$ is independent of other counties' disasters (assuming no contagion), the supply-side credit contraction should put upward pressure on $r_{k'}$. However, demand-side forces may offset this through "wait-and-see" behavior (Bloom et al., 2007): uncertainty about disaster propagation may reduce firms' investment demand in unaffected regions, shifting loan demand inward. The net effect depends on relative elasticities.

Empirical Prediction (Hypothesis 4): The ambiguous theoretical prediction generates Hypothesis 4.

B.3. Triadic Coordination Mechanism

B.3.1. Bilateral Relationships and Hold-up Problems

Strong borrower-lead relationships (R_{ij}^{BL}) enable the lead to acquire precise information about firm quality. However, this creates a hold-up problem: participants who lack relationships with the lead (R_j^{PL} low) cannot verify whether the lead is sharing information honestly. Anticipating adverse selection, participants demand higher participation shares or refuse to participate, constraining credit supply.

Conversely, strong participant-lead relationships (R_j^{PL}) build trust in the lead's general competence but cannot substitute for lack of borrower-specific information when R_{ij}^{BL} is low.

Formally, the lead's incentive compatibility constraint for truthful information sharing is:

$$\underbrace{\alpha_{ij}[r_i(\sigma_i) - \rho_{ik}]I_i}_{\text{Honest strategy payoff}} \geq \underbrace{\alpha_{ij}[r_i(\hat{\sigma}_i) - \rho_{ik}^{bad}]I_i - \Omega_j(R_j^{PL})}_{\text{Deviation payoff}} \tag{B18}$$

where $\hat{\sigma}_i$ is a false signal, ρ_{ik}^{bad} is the risk premium on low-quality loans the lead retains, and $\Omega_j(R_j^{PL})$ is the reputation cost of detected deviation.

Rearranging:

$$\alpha_{ij} \geq \frac{\Omega_j(R_j^{PL})}{[r_i(\hat{\sigma}_i) - \rho_{ik}^{bad}]I_i - [r_i(\sigma_i) - \rho_{ik}]I_i} \tag{B19}$$

Strong participant-lead relationships (high R_j^{PL}) increase reputation capital Ω_j, raising the cost of opportunism and enabling the lead to retain smaller shares while credibly syndicating higher volumes.

However, without borrower-lead relationships (R_{ij}^{BL} low), the lead lacks precise information to share. Even with strong reputation (Ω_j high), participants face elevated risk from the lead's genuine uncertainty about borrower quality, constraining participation.

B.3.2. Triadic Coordination Benefits

When both relationship dimensions are strong (R_{ij}^{BL} high and R_j^{PL} high), three complementary mechanisms operate:

1. **Information Acquisition:** Strong borrower-lead ties enable precise signal extraction: $\sigma^2(e_{ij}, R_{ij}^{BL})$ is minimized when R_{ij}^{BL} is high.

2. **Credible Signaling:** Strong participant-lead ties enable the lead to credibly communicate private information through reputation $\Omega_j(R_j^{PL})$.

3. **Cross-Monitoring:** Participants observe the lead's historical performance with this specific borrower, enabling reputation updating based on realized outcomes: $\Omega_{j,t+1} = \Omega_{j,t} - \xi \cdot \mathbb{1}\{\text{default}\}$ where $\xi > 0$ penalizes defaults.

The interaction effect arises because borrower-lead and participant-lead relationships are complements: the marginal value of borrower-lead information increases when the lead can credibly signal it to participants, and the marginal value of participant-lead trust increases when the lead possesses valuable information to share.

Formally, total credit supply to firm i is:

$$I_i = I_0 + \beta_1 R_{ij}^{BL} + \beta_2 R_j^{PL} + \beta_3 (R_{ij}^{BL} \times R_j^{PL}) \tag{B20}$$

We can derive sign predictions. From the hold-up problem when R_{ij}^{BL} is high but R_j^{PL} is low, participants rationally reduce participation, implying $\beta_1 < 0$ in isolation. From the information gap when R_j^{PL} is high but R_{ij}^{BL} is low, uninformed lending remains risky, potentially implying $\beta_2 < 0$ in some contexts (though reputation alone may generate

$\beta_2 > 0$). However, the interaction coefficient $\beta_3 > 0$ because relationship dimensions are complementary in resolving information frictions.

Proposition 3 (Triadic Coordination in Credit Allocation)**.** *In syndicated lending equilibrium:*

(i) Bilateral relationships may individually reduce credit supply ($\beta_1 \leq 0$, β_2 ambiguous) due to hold-up problems and information gaps.

(ii) The interaction of borrower-lead and participant-lead relationships increases credit supply ($\beta_3 > 0$) through complementary information acquisition, credible signaling, and cross-monitoring.

(iii) The triadic effect dominates bilateral frictions: $|\beta_3| > |\beta_1| + |\beta_2|$ when both relationships are sufficiently strong.

Empirical Predictions (Hypotheses 5a and 5b): Proposition 3 parts (i) and (ii) generate Hypotheses 5a and 5b.

For loan pricing, triadic coordination reduces the risk premium through three channels: lower screening costs (the lead exerts higher effort due to better information), lower information asymmetry (credible signaling reduces participants' uncertainty), and lower monitoring costs (cross-monitoring substitutes for costly direct monitoring). This generates:

Proposition 4 (Triadic Coordination in Loan Pricing)**.** *The risk premium decreases with triadic relationship strength:*

$$\rho_{ik} = \rho_0 + \lambda\delta_k - \gamma_1 R_{ij}^{BL} - \gamma_2 R_j^{PL} - \gamma_3 (R_{ij}^{BL} \times R_j^{PL}) \tag{B21}$$

where $\gamma_3 > 0$ captures the complementary effect on information frictions.

Empirical Prediction (Hypothesis 5c): Proposition 4 generates Hypothesis 5c, predicting negative association between triadic relationships and loan spreads.

B.4. Market Failure and Public Assistance

B.4.1. Pareto Inefficiency of Competitive Equilibrium

A social planner maximizes aggregate output across all counties subject to the same aggregate credit constraint:

$$\max_{\{s_k\}} \sum_k Y_k = \sum_k A_k K_k^{\beta} \quad \text{subject to} \quad \sum_k s_k = 1 \tag{B22}$$

The planner's first-order condition equates marginal products of capital across regions:

$$MPK_k = MPK_{k'} \quad \forall k, k' \tag{B23}$$

Comparing to the competitive equilibrium condition (B14):

$$\begin{aligned}\text{Competitive:} \quad & MPK_k - \rho_k - \kappa s_k = MPK_{k'} - \rho_{k'} - \kappa s_{k'} && \text{(B24)}\\ \text{Planner:} \quad & MPK_k - \kappa s_k = MPK_{k'} - \kappa s_{k'} && \text{(B25)}\end{aligned}$$

The wedge is the risk premium term $\rho_k - \rho_{k'}$. From the competitive condition:

$$MPK_k - MPK_{k'} = \rho_k - \rho_{k'} + \kappa(s_k - s_{k'}) \tag{B26}$$

For a disaster-affected county k with $\delta_k > 0$ and unaffected county k' with $\delta_{k'} = 0$:

$$\rho_k - \rho_{k'} = \lambda\delta_k - \gamma(R_k - R_{k'}) > 0 \tag{B27}$$

assuming similar relationship capital across counties, where $R_k \equiv \frac{1}{N_k}\sum_{i\in k,j}(R_{ij}^{BL} + R_j^{PL})/2$ represents average relationship capital between firms in county k and their lenders, with N_k being the number of firm-bank pairs in county k.[13] This implies:

$$MPK_k - MPK_{k'} > \kappa(s_k - s_{k'}) \tag{B28}$$

By strict concavity of production ($Y_k'' < 0$), this inequality holds only if the competitive allocation under-allocates to disaster region: $s_k^{CE} < s_k^{SP}$.

Theorem 1 (Pareto Inefficiency)**.** *Competitive equilibrium systematically under-allocates credit to disaster-affected counties relative to the social optimum. The misallocation gap is:*

$$s_k^{SP} - s_k^{CE} = \frac{\rho_k - \rho_{k'}}{|Y_k''| + |Y_{k'}''| + 2\kappa} = \frac{\lambda\delta_k - \gamma(R_k - R_{k'})}{|Y_k''| + |Y_{k'}''| + 2\kappa} \tag{B29}$$

The gap increases with disaster intensity ($\partial/\partial\delta_k > 0$) and decreases with relationship capital ($\partial/\partial R_k < 0$).

The welfare loss from misallocation is:

$$\Delta W = \int_{s_k^{CE}}^{s_k^{SP}} [MPK_k(x) - MPK_{k'}(1-x)]dx \approx \frac{1}{2}\frac{(\rho_k - \rho_{k'})^2}{|Y_k''| + |Y_{k'}''|} \tag{B30}$$

This quadratic loss formula shows welfare costs increase with the square of the risk premium wedge.

[13] This aggregation from firm-bank level to county level is reasonable when relationship capital is relatively homogeneous within counties, or when we interpret R_k as capturing the average network strength available to firms in county k.

B.4.2. Public Assistance as Partial Correction

Public disaster assistance operates through multiple channels that reduce the risk premium wedge. FEMA grants G_k to county k affect the risk premium through:

$$\rho_k(\delta_k, G_k, R_k) = \rho_0 + \lambda\delta_k - \gamma R_k - \xi G_k \tag{B31}$$

where $\xi > 0$ captures the risk-mitigation effect of public assistance through:

1. **Cash flow stabilization:** Direct grants improve firms' debt capacity and reduce default probability
2. **Collateral restoration:** Insurance payouts restore damaged assets
3. **Infrastructure repair:** Public infrastructure investments reduce business disruption risk
4. **Uncertainty reduction:** Federal commitment to regional recovery reduces perceived tail risks

From Theorem 1, the misallocation gap becomes:

$$s_k^{SP} - s_k^{CE}(G_k) = \frac{\lambda\delta_k - \gamma R_k - \xi G_k}{|Y_k''| + |Y_{k'}''| + 2\kappa} \tag{B32}$$

Public assistance reduces the gap:

$$\frac{\partial[s_k^{SP} - s_k^{CE}]}{\partial G_k} = \frac{-\xi}{|Y_k''| + |Y_{k'}''| + 2\kappa} < 0 \tag{B33}$$

Proposition 5 (Public Assistance Reduces Misallocation)**.** *FEMA public assistance reduces the gap between competitive and socially optimal credit allocation:*

$$\frac{\partial[s_k^{SP} - s_k^{CE}]}{\partial G_k} < 0 \tag{B34}$$

The reduction is proportional to the risk-mitigation effectiveness ξ and inversely proportional to output curvature and adjustment costs.

Empirical Prediction (Hypothesis 6): Proposition 5 generates Hypothesis 6.

However, public assistance provides only partial correction. Even with substantial FEMA grants, a residual gap persists because:

1. Public assistance is imperfect substitute for private risk-bearing: $\xi G_k < \lambda\delta_k$ for feasible G_k
2. Relationship capital provides complementary but incomplete insurance: γR_k cannot fully offset disaster risk

3. Binding credit constraints prevent full adjustment even if risk premia are eliminated

The model predicts that moving from low to high public assistance (e.g., 10th to 90th percentile) reduces but does not eliminate the misallocation gap, consistent with the empirical finding of 24% reduction with 76% residual gap documented in Section 4.10.

B.5. Summary of Theoretical Predictions

Table B1 maps the theoretical propositions to empirical hypotheses tested in the main text.

Table B1: Mapping of Theoretical Propositions to Empirical Hypotheses

Theoretical Result	**Key Prediction**	**Empirical Hypothesis**
Proposition 1 (Credit Reallocation)	$\frac{\partial s_k}{\partial \delta_k} > 0$ when productivity effect dominates	Hypothesis 1: Positive disaster-lending association
Equation (B11) (Risk Premium)	$\frac{\partial \rho_k}{\partial \delta_k} = \lambda > 0$	Hypothesis 2: Positive disaster-spread association
Proposition 2 (Spillover Effects)	$\frac{\partial s_{k'}}{\partial PExposure} < 0$ for unaffected k'	Hypothesis 3: Negative spillover on lending
Spillover interest rates	Ambiguous: supply ↑ vs. demand ↓	Hypothesis 4: Ambiguous spillover on spreads
Proposition 3 part (i) (Bilateral Frictions)	$\beta_1 \leq 0$, β_2 ambiguous	Hypothesis 5a: Bilateral relationships reduce lending
Proposition 3 part (ii) (Triadic Coordination)	$\beta_3 > 0$ with $\lvert\beta_3\rvert > \lvert\beta_1\rvert + \lvert\beta_2\rvert$	Hypothesis 5b: Triadic interaction increases lending
Proposition 4 (Pricing)	$\gamma_3 > 0$: triadic reduces spreads	Hypothesis 5c: Triadic interaction reduces spreads
Theorem 1 & Proposition 5 (Market Failure)	$\frac{\partial [s^{SP} - s^{CE}]}{\partial G_k} < 0$	Hypothesis 6: FEMA reduces misallocation gap

Notes: This table summarizes the mapping between theoretical propositions derived in this appendix and empirical hypotheses tested in the main text. All propositions are derived assuming competitive syndicated loan markets with disaster shocks, asymmetric information, and binding credit constraints. The model microfounds the triadic coordination mechanism through complementarities in information acquisition (borrower-lead ties), credible signaling (participant-lead ties), and cross-monitoring (interaction of both).

B.6. Microfoundation: Repeated-Game Equilibrium for Relationship Capital

The preceding analysis treated relationship capital R_{ij}^{BL} and R_j^{PL} as exogenous. This section microfounds these relationships through infinitely-repeated games with self-enforcing contracts, justifying their treatment as predetermined variables in our empirical specifications since they are built over three-year windows preceding loan originations.

B.6.1. Borrower-Lead Relationship Formation

Consider an infinite-horizon game between borrower i and lead arranger j with discount factor $\beta \in (0,1)$. Each period, the borrower needs financing I and the lead chooses screening effort $e \in [0,1]$ at cost $c(e) = \frac{\psi e^2}{2}$.

Stage game payoffs:

- If lead exerts effort e and borrower repays (conditional on project success): Lead receives $(1+r)I - I - c(e) = rI - \frac{\psi e^2}{2}$; Borrower receives $MPK \cdot I - (1+r)I$
- If borrower defaults strategically (when able): Lead receives 0; Borrower receives $MPK \cdot I$

Grim trigger strategies:

- Lead: Exert effort e^* if all past interactions resulted in repayment when projects succeeded; otherwise exert $e = 0$ (cease relationship)
- Borrower: Repay if project succeeds and lead has maintained effort e^*; otherwise default

For the lead, maintaining effort e^* must be preferable to deviating to $e = 0$. The present value of cooperation must exceed the one-period deviation payoff (which includes the interest received $(1 - p_d(0))rI$ with zero screening cost) followed by relationship termination:

$$\frac{(1 - p_d(e^*))rI - \frac{\psi(e^*)^2}{2}}{1-\beta} \geq (1 - p_d(0))rI \tag{B35}$$

Rearranging, the sustainable effort level e^* must satisfy the implicit condition:

$$e^* \leq \sqrt{\frac{2\beta(1 - p_d(e^*))rI}{\psi(1-\beta)}} \tag{B36}$$

Note: This is an implicit equation defining the equilibrium effort level. The right-hand side depends on e^* through $p_d(e^*)$, so this condition characterizes the fixed point that determines sustainable screening effort.

For the borrower, repaying must be preferable to defaulting:

$$MPK \cdot I - (1+r)I + \frac{\beta}{1-\beta}[MPK \cdot I - (1+r)I] \geq MPK \cdot I \tag{B37}$$

This simplifies to:

$$\frac{\beta}{1-\beta} \geq \frac{(1+r)I}{MPK \cdot I - (1+r)I} \tag{B38}$$

The relationship can be sustained when both incentive constraints hold. Define relationship capital as the strength of these self-enforcing incentives:

$$R_{ij}^{BL} \equiv \frac{\beta}{1-\beta} \cdot \frac{MPK \cdot I - (1+r)I}{(1+r)I} \tag{B39}$$

Higher β (more patient parties), higher MPK (more productive projects), and lower default risk all increase relationship capital, enabling higher sustainable effort e^* and thus lower risk premia $\rho = p_d(e^*)LGD$.

B.6.2. Participant-Lead Relationship and Reputation

Participants cannot directly observe lead screening effort or private signals. However, they observe ex-post loan performance across their portfolios of syndicated deals with lead j. Let $\theta_j \in \{\text{honest}, \text{dishonest}\}$ denote the lead's type (unobservable).

Honest leads truthfully report signals σ_i and exert optimal effort. Dishonest leads may misreport signals to syndicate low-quality loans while retaining high-quality loans. Participants form beliefs $\pi_t(\theta_j = \text{honest})$ based on historical performance.

With repeated interactions, participants update beliefs using Bayes' rule. A proper Bayesian updating formulation is:

$$\pi_{t+1} = \begin{cases} \frac{\pi_t(1-p_H)}{[\pi_t(1-p_H)+(1-\pi_t)(1-p_L)]} & \text{if no default} \\ \frac{\pi_t p_H}{[\pi_t p_H+(1-\pi_t)p_L]} & \text{if default occurs} \end{cases} \tag{B40}$$

where p_H is the default probability under an honest lead (typically low) and p_L is the default probability under a dishonest lead (typically high). When $p_H < p_L$, good performance (no default) increases π_t while defaults decrease it.

Define participant-lead relationship capital as accumulated reputation:

$$R_j^{PL} = \pi_\infty(\theta_j = \text{honest} \mid \text{history}) = \lim_{t\to\infty} \pi_t \tag{B41}$$

Strong participant-lead relationships (R_j^{PL} high) enable the lead to credibly syndicate larger shares because participants trust the lead's information sharing based on historical track record.

B.6.3. Complementarity of Relationship Dimensions

The marginal value of borrower-lead relationships increases with participant-lead relationships:

$$\frac{\partial^2 I}{\partial R_{ij}^{BL} \partial R_j^{PL}} = \frac{\partial^2}{\partial R_{ij}^{BL} \partial R_j^{PL}}[I_0 + \beta_1 R_{ij}^{BL} + \beta_2 R_j^{PL} + \beta_3 R_{ij}^{BL} \cdot R_j^{PL}] = \beta_3 > 0 \tag{B42}$$

This complementarity arises because:

1. Better borrower-specific information (from high R_{ij}^{BL}) has greater value when the lead can credibly syndicate it (high R_j^{PL})
2. Participant trust (from high R_j^{PL}) generates larger syndication capacity when the lead possesses valuable private information (high R_{ij}^{BL})

The triadic structure emerges endogenously as the equilibrium of the repeated game when all three parties maintain sufficiently strong relationships to support cooperation along both dimensions simultaneously.

B.7. Extensions and Robustness

B.7.1. Heterogeneous Disaster Intensities

The model can accommodate heterogeneous disaster intensities $\delta_k \sim F(\cdot)$ drawn from a distribution. The comparative statics remain qualitatively similar, with lending shares and spreads responding continuously to δ_k. The key insight—that credit reallocates toward disaster regions when productivity effects dominate risk effects—holds across the distribution of disaster intensities.

B.7.2. Multiple Lead Arrangers and Syndicate Competition

With multiple competing leads, the model extends naturally by incorporating Bertrand competition for borrowers. The zero-profit condition becomes:

$$r_i = r_f + \min_j \{\rho_{ijk}(R_{ij}^{BL}, R_j^{PL}, \delta_k)\} \tag{B43}$$

Borrowers select the lead offering the lowest interest rate, which depends on relationship capital along both dimensions. This amplifies the importance of triadic coordination: leads with weak relationships on either dimension face competitive disadvantage, creating incentives to build relationships along both dimensions simultaneously.

B.7.3. Dynamic Relationship Formation

The static model treats relationship capital as given. In a dynamic extension, banks and borrowers would invest in relationship formation by accepting lower short-run returns in exchange for information advantages and reputation benefits in future periods. The optimal investment in relationships would trade off current costs against the present value of future coordination benefits, generating predictions about relationship persistence and the evolution of syndicate networks over time.

This appendix has provided theoretical microfoundations for the empirical patterns documented in the main text. The model demonstrates that:

1. Disasters create a productivity-risk trade-off in credit allocation, with lending shares increasing when productivity effects dominate (Proposition 1)

2. Binding credit constraints generate spillover effects in unaffected regions as banks reallocate portfolios (Proposition 2)

3. Triadic coordination among borrowers, lead arrangers, and participants is essential for efficient syndicated lending under information asymmetry (Propositions 3 and 4)

4. Competitive equilibrium systematically under-allocates credit to disaster regions, with public assistance providing partial but incomplete correction (Theorem 1 and Proposition 5)

These theoretical results provide the foundation for the empirical hypotheses tested in Sections 4 through 4.10, with the mapping formalized in Table B1. The repeated-game microfoundations demonstrate that relationship capital emerges endogenously from self-enforcing contracts when parties interact repeatedly, grounding the treatment of relationship variables as predetermined in our empirical specifications since they are built over three-year windows preceding loan originations.