

**ANCHORING RESILIENCE:
HOW THREATS SHAPE THE CAPACITY OF COMMUNITY ORGANIZATIONS**

A dissertation presented

By

Allison Donine Deese

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In partial fulfillment of the requirements for the degree of

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Northeastern University

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ABSTRACT OF DISSERTATION

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ABSTRACT

Community-based organizations (CBOs) are widely recognized as the backbone of community-level preparedness and resilience. They are the first and last point of support when major disruptions occur, and they play a critical role in long-term recovery. Despite this, the capacity of CBOs to withstand disruption is more often assumed and rarely studied directly (De Oro 2025). This dissertation asks how cumulative threat exposure shapes both the communities in which CBOs are embedded and the organizational strategies and capacities through which they sustain their work.

Using national county-level data on social capital and disaster exposure, along with in-depth interviews with 50 CBO leaders across the United States and an organizational survey (n = 51, with 21 organizations completing both), this dissertation investigates three central research questions: (1) Does recurrent disaster exposure measurably change county-level social capital in the United States, either by increasing or eroding its overall level, or by shifting its composition across bonding, bridging, and linking dimensions? (2) How do different threat environments shape the resilience capacities that CBOs build, activate, or draw down? And (3) Among CBOs that continue operating through repeated pressures, what allows some organizations to preserve or rebuild internal capacity while others draw down staff, reserves, mission scope, infrastructure, or leadership capacity?

The findings in this dissertation unfold from the community-level context to the organizational level. Paper 1 finds that recurrent FEMA-declared disaster exposure does not measurably alter aggregate social capital. Disaster-prone counties differ from less exposed counties in cross-section, but the analysis finds little evidence that repeated disasters produce meaningful within-county change in bonding, bridging, linking, or composite social capital. This

suggests that community social capital is relatively stable at the national county scale, rather than a measurable response to disaster exposure.

At the organizational level, disruption appears more clearly inside the CBOs that sustain local support systems. The second paper develops the Organizational Resilience Threat-Informed Investment Framework (OR-TIIF) for understanding how CBOs build and use resilience capacity across diverse and compounding threat environments. The framework begins with the threats an organization faces and maps the capacities it builds, activates, or draws down in response. Financial, technological, and staffing threats generally prompt investment in the corresponding capacity. Health and demand shocks are more often absorbed through operational change, while planning concentrates around forecastable hazards. Social capacity operates across threat types as standing relational infrastructure. Political and regulatory threats mark the limits of internal capacity-building because organizations cannot always address a hostile policy shift or regulatory constraint through internal investment.

The third paper examines the condition in which CBOs continue operating through repeated pressures. Because every organization in the study remained open, continued service alone could not distinguish organizations preserving or rebuilding capacity from those consuming resources they could not replace. The paper therefore classifies organizations as thriving, recovering, in strained continuity, or in depleted continuity. These categories reflect financial condition, staffing and operational capacity, and whether the organization was improving, stable, or worsening. Some CBOs maintained or rebuilt both financial and organizational capacity. Others remained open by exhausting staff, depleting reserves, narrowing mission scope, deferring infrastructure investments, or relying on unpaid leadership labor. Relational support helped organizations persist across all four conditions, though it did not

distinguish organizations with sustainable capacity from those in depleted continuity.

Organizations that preserved capacity more often had financial buffers, adequate staffing, durable operational systems, and time to recover between disruptions.

Together, the three papers show that resilience must be understood at both the community and organizational levels. Stable county-level social capital does not show how individual CBOs on the ground experience and absorb disruption. The organizational analyses trace how different threats shape the capacities CBOs build, activate, or draw down. They also reveal that continued operation can conceal substantial differences in operational condition. Thus, this dissertation argues for a threat-informed, condition-level approach to resilience. This approach asks which threats organizations face, how they respond, and what is strengthened, strained, or depleted as they continue serving their communities.

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shown me what truly thoughtful, successful community-engaged research looks like, and how to gracefully manage the demands of multiple ongoing projects. I have relied deeply on her guidance throughout the course of my dissertation.

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TABLE OF CONTENTS

Abstract.....	3
Acknowledgements.....	6
List of Tables and Figures.....	15

Introduction

1. Research Motivation.....	17
1.1. Research Questions.....	19
2. Methods Overview.....	20
2.1. Research Design.....	20
2.2. Sampling Strategy.....	21
2.3. Data Collection.....	23
2.4. Data Analysis.....	25
2.4.1. County-Level Analysis.....	25
2.4.2. Qualitative Analysis.....	26
2.4.3. Survey Analysis.....	27
2.5. Ethical Considerations.....	27
2.6. AI in the Research Process.....	28
References.....	33

Paper 1: Stable Ground: Recurrent Disaster Exposure and County-Level Social Capital in the United States

Abstract.....	36
1. Introduction.....	37
2. Background.....	39

2.1.	Social Capital Shapes Disaster Outcomes.....	40
2.2.	Organizational Infrastructure as Social Capital.....	40
2.3.	Disaster Effects on Social Capital Vary by Context and Dimension.....	42
2.4.	Rationale for a Multidimensional Social Capital Index.....	43
3.	Methods.....	45
3.1.	Data and Sample.....	45
3.2.	Social-Capital Measurement.....	46
3.3.	FEMA-Declared Disaster Exposure.....	49
3.4.	Estimating the Relationship Between Disaster Exposure and Social Capital.....	51
3.5.	Preregistration.....	53
4.	Results.....	54
4.1.	No Meaningful Association Between Disaster Exposure and Composite Social Capital.....	54
4.2.	The Null Result is Consistent Across Estimators.....	55
4.3.	The Exposure Gap Narrows After Matching.....	57
4.4.	No Consistent Pattern Across Social Capital Subindices.....	57
4.5.	Secondary and Sensitivity Analyses Leave the Main Finding Unchanged.....	59
5.	Discussion.....	61
5.1.	Limitations.....	64
5.2.	Future Research.....	65
6.	Conclusion.....	66
	References.....	68

Paper 2: Threat-Informed Investment: A Diagnostic Framework for Resilience in Community-Based Organizations

Abstract.....	76
1. Introduction.....	77
2. Background.....	81
2.1. External Context Recognized, but Undertheorized.....	81
2.2. Gaps in Nonprofit Resilience Frameworks.....	83
2.3. Threat Environments and Resource Dependence.....	87
2.4. The Limits of General Capacity Assessments.....	89
2.5. How the OR-TIIF Differs from Scenario Planning.....	90
3. Methods.....	91
3.1. Study Design and Sample.....	91
3.2. Unit of Analysis: Threat-Response Episodes.....	94
3.3. Coding Capacity Investments.....	94
3.4. Developing the OR-TIIF.....	96
3.5. Reliability and Scope.....	100
3.6. Framework Structure and Output.....	101
4. Findings.....	104
4.1. CBOs Face Diverse and Cumulative Threats.....	104
4.2. Threats Often Prompt Matching Capacity Investments.....	106
4.3. Health and Demand Threats Prompt Operational Change.....	108
4.4. Planning Centers on Forecastable Threats.....	108
4.5. Social Capacity Functions as Standing Infrastructure.....	109

4.6.	Political and Regulatory Threats Prompt Tactics, Not Capacity Investment.....	111
4.7.	Mode and Approach Produce Four Investment Postures.....	112
5.	Discussion.....	117
5.1.	Resilience as Threat-Informed Investment.....	117
5.2.	Political Threats and the Limits of Internal Capacity.....	119
5.3.	The OR-TIIF as a Diagnostic Tool.....	120
5.4.	Limitations.....	121
5.5.	Future Research	122
6.	Conclusion.....	122
	References.....	124

Paper 3: The Hidden Costs of Persistence in Community-Based Organizations

	Abstract.....	130
1.	Introduction.....	131
2.	Background.....	133
2.1.	Resilience as a Capability, Process, Outcome, and Condition.....	133
2.2.	Financial Health and Operational Condition.....	135
2.3.	Relational Support and CBO Persistence.....	137
3.	Data and Methods.....	140
3.1.	Sample and Fieldwork Context.....	140
3.2.	Classifying Operational Condition.....	141
3.3.	Coding Supports and Pressures.....	144
3.4.	Targeted Coding of Potential Explanations for Operational Condition.....	146
3.5.	AI-Assisted Coding and Manual Verification Process.....	146

3.6.	Analytic Approach and Scope.....	147
4.	Findings.....	147
4.1.	Four Operational Conditions.....	148
4.2.	Relational Support Sustains Persistence Across Conditions.....	151
4.3.	Internal Capacity and Recovery Distinguish Thriving from Depleted Continuity.....	152
4.4.	Leader Self-Assessments Can Obscure Operational Depletion.....	156
5.	Discussion and Implications.....	158
6.	Limitations.....	159
7.	Conclusion.....	160
	References.....	162
Conclusion		169
1.	Summary of Findings.....	169
2.	Contributions and Implications.....	170
3.	Future Research.....	171
4.	Sustaining CBO Resilience.....	173
	References.....	175

LIST OF TABLES AND FIGURES

Introduction

Table 1. Participant Response Rates.....	25
--	----

Paper 1

Table 1. Social Capital Measures and Sources.....	48
Figure 1. Change in FEMA-Declared Exposure Across ACS Windows.....	50
Table 2. Composite SoCI Estimates Across Analyses.....	56
Table 3. Subindex Estimates From the Same-Window Fixed-Effects Model.....	58

Appendix: Supplemental Tables

Table 1. SoCI Indicator Crosswalk.....	72
Table 2. County Panel Construction and Exclusions.....	73
Table 3. Full Preregistered Results.....	74
Table 4. Robustness and Exploratory Disclosures.....	75

Paper 2

Figure 1. Sample Demographics.....	92
Table 1. OR-TIIF Domains, Analytic Roles, and Indicators.....	101
Figure 2. OR Threat-Informed Investment Framework (OR-TIIF).....	103
Figure 3. Threat-Response Episodes by Threat Type.....	105
Figure 4. Capacity Investments by Threat Type.....	107
Figure 5. Social Capacity Across Threat Types.....	110
Figure 6. Political and Regulatory Threats Mark the Limits of Capacity Investment....	112
Figure 7. Four Investment Postures by Mode and Approach.....	113
Table 2. Four OR-TIIF Investment Postures.....	114

Figure 8. Investment Approach by Threat Type.....	115
---	-----

Paper 3

Figure 1. Sample Demographics	141
Table 1. Operational Condition Classifications.....	143
Table 2. Supports and Pressures by Factor Category.....	144
Figure 2. The Financial Axis × Capacity Axis.....	149
Figure 3. Framework for Classifying Operational Condition.....	151
Figure 4. Recovery Windows and Staffing Protection by Operational Condition.....	156

Appendix: Supplemental Tables

Table 1. Factor Attributions by Analytic Family, Direction, and Operational Condition.....	165
Table 2. Illustrative Evidence for Condition-Shaping Factors.....	166
Figure 1. Protective and Depleting Factors by Operational Condition.....	168

INTRODUCTION

“Organizational resilience is inherently context-sensitive, yet empirical research has only begun to systematically examine how contextual variables shape the development and enactment of resilience.” (Raetze et al. 2022)

1. Research Motivation

In 2014, I lived in Jure, a village in the Sindhupalchowk District of Nepal for two weeks. It had been three months since a catastrophic landslide struck the village, burying 159 people. I was there to study the gendered impacts of the landslide on women and children in the surrounding community, in partnership with a local development organization that had agreed to house me and support my qualitative research. During community interviews, I became acutely aware of how erroneous assumptions made by predominantly male emergency managers could lead to disastrous outcomes for women and their children. The organization I collaborated with was essential in mitigating these gaps by promoting women’s long-term recovery, supporting their involvement in relocation discussions, and educating families on the increased risk of sex trafficking. My undergraduate research in Nepal was an entry point for better understanding the critical role of community-based organizations (CBOs) during periods of crisis and long-term recovery, and the everyday challenges CBO staff face on an emotional and organizational level to meet community members’ needs.

Before beginning my PhD program at Northeastern, I spent four years in communities highly vulnerable to climate-induced disruption. I chose to live and work in these places because I wanted a deeper, more nuanced understanding of both the challenges they faced and the capacities and opportunities within them, so that any research I later pursued would be grounded in sustained engagement and not abstract assumptions. I lived in Vietnam’s Mekong Delta less than a year after the region experienced its most severe drought in over a century (Open

Development Vietnam 2022); worked for the American Red Cross in Northern California in 2017, during what was then the most destructive wildfire year on record in the state (Cal Fire 2017); and spent two years as a Coastal Resource Management Peace Corps volunteer in the Philippines, one of the countries most exposed to severe climate impacts (NICCDIES n.d.).

Across these experiences, disruptive events rarely appeared as isolated shocks. Communities affected by one disaster were often still recovering from a prior disruption when the next arrived. The Jure Landslide was followed less than a year later by the 2015 earthquake in Nepal; the 100-year drought of 2015-16 in Vietnam was followed by an even more severe one in 2019–20; the 2021 Dixie Fire overlapped with COVID-19; and a volcano was erupting in the Philippines as I was being evacuated for the pandemic. In addition to responding to acute crises as they arose, the local organizations I worked with were also managing chronic community needs, staff fatigue, financial uncertainty, and limited planning capacity. My earlier doctoral work in Butte County, California, following COVID-19 and repeated mega-wildfire seasons, further clarified this pattern. Organizational resilience is not only about physical infrastructure, sound policies, or formal preparedness. It is also deeply relational.

CBOs are the foundation of community resilience. Unlike larger nonprofit organizations or national aid organizations, CBOs maintain a continuous presence that allows them to maintain legitimacy over time (Rivera and Nickels 2014). They are typically resident-led, self-governing, and nonprofit-distributing (Wilson, Lavis, and Guta 2012). CBOs also tend to be smaller and less bureaucratic, providing them with greater flexibility to adapt operations quickly (Simo and Bies 2007; Murphy 2014). They include advocacy groups, charities, faith-based organizations, cultural organizations, and direct social service providers, and are often formed by community members to address local

issues in low- or moderate-income areas (DiMaggio and Anheier 1990; Walker 2022). CBOs build trust and solidarity within their communities, enhancing their ability to identify and respond to diverse needs during disaster response and recovery (Chillag et al. 2002; De Vita et al. 2008; Atkinson 2014; Demiroz and Hu 2014).

This dissertation seeks to investigate how the locally rooted organizations that communities rely on understand and sustain their own resilience, especially when disruption is recurring and cumulative, with little time for recovery between events. I examine CBOs not only as contributors to community resilience, but as organizations whose own resilience must be built and maintained under pressure. If communities depend on CBOs during crisis and recovery, then the capacity of CBOs to keep doing that work should not be taken for granted. This dissertation therefore turns to CBO leaders themselves, asking how they experience disruption, how they respond, and what challenges they face as they build and maintain the internal capacities that allow their organizations to continue serving their communities.

1.1. Research Questions

Across the three papers, I move from county-level patterns, to organizational resilience processes, to an analysis of organizations' current operating condition. This dissertation project argues that community resilience rests on how local organizations understand threats, what capacities they build or draw down, and what operational condition they remain in while continuing to provide services. The following three research questions are addressed in this dissertation:

- (1) Does recurrent disaster exposure measurably change county-level social capital in the United States, and if so, does that change appear as growth, erosion, or reorganization across bonding, bridging, and linking dimensions? (Paper 1)
- (2) How do different threat environments shape the resilience capacities that CBOs build, activate, or draw down? (Paper 2)
- (3) Among CBOs that continue operating through repeated pressures, what allows some organizations to preserve or rebuild internal capacity while others draw down staff, reserves, mission scope, infrastructure, or leadership capacity? (Paper 3)

2. Methods Overview

Scholars call for research that “explores the range and nature of adverse situations in today's organizations as well as adequate investigations of the essential processes involved in entities' reactions to such challenges” (Raetz et al. 2022:889). This dissertation responds by examining how community-based organizations (CBOs) invest in capacity across varied threat environments and what condition they remain in as they continue their work. These questions required a multimethod design that combined longitudinal county analysis, organizational interviews, and a short survey. This section summarizes the research design, sampling strategy, data collection, analytic procedures, ethical safeguards, and use of artificial intelligence.

2.1. Research Design

This dissertation consists of three coordinated studies that share a research problem and sampling infrastructure while remaining analytically distinct. Paper 1 uses a balanced panel of 3,133 U.S. counties and county-equivalent units observed across three periods. It tests whether recurrent FEMA-declared disaster exposure changes county-level social capital. Papers 2 and 3

draw on interviews with leaders of CBOs, supplemented by an organizational survey. They examine how CBOs respond to varied threats and what operational condition they remain in while continuing to serve their communities.

The county disaster-exposure classification also guided recruitment for the organizational study. I linked the two studies at the design stage, in which the county-level disaster-exposure classification constructed for the panel analysis also stratified the organizational sample. Each paper's analysis is independent, and I bring the findings into conversation in the opening and closing sections rather than within the papers themselves.

The county study follows a deductive design. The final analysis plan was preregistered under the conditions described in Section 2.4.1. The organizational study is abductive. It uses leaders' accounts to examine how organizations understand threats, invest in capacity, and absorb the costs of continued operation. The survey provides standardized descriptive evidence and a limited comparison with patterns identified in the interviews. Large administrative datasets cannot capture these processes.

This design reflects the multilevel structure of the research questions. Longitudinal county data are needed to determine whether recurrent disasters change aggregate social capital. Organizational accounts are needed to identify how CBOs experience disruption, respond to it, and maintain or deplete internal capacity. The combined design therefore distinguishes county-level patterns from the organizational processes that aggregate and large administrative datasets cannot capture.

2.2. Sampling Strategy

The county panel consists of all 3,133 U.S. counties and county-equivalents, observed in each of three American Community Survey (ACS) 5-year periods: 2006–2010, 2012–2016, and 2018–2022.

The organizational study used a purposive, multistage stratified sampling strategy designed to capture variation in threat environment and disaster exposure. Recruitment initially focused on four areas defined by predominant hazard profile: the West Coast (wildfire), the Gulf Coast (hurricanes), New England (severe storms and flooding), and the Southeast/Midwest, expanded during fieldwork to capture tornado exposure and western North Carolina communities affected by Hurricane Helene. Within these areas, I classified counties into three disaster-exposure strata using FEMA major-disaster declarations from 2014 through 2023. COVID-19 declarations were excluded. High-frequency, high-recency counties averaged one year or less between declarations and had at least three declarations after 2019. Moderate-frequency, high-recency counties averaged between one and one-and-a-half years and also had at least three declarations after 2019. Low-frequency, low-recency counties averaged more than one-and-a-half years between declarations and had fewer than three after 2019. To avoid concentrating the exposure strata in a single economic context, I balanced recruitment across population and poverty tertiles calculated within each region. These measures came from the 2019–2023 American Community Survey estimates.

Eligible organizations were CBOs engaged in direct service, advocacy, organizing, or intermediary support. They were generally small or medium-sized, with fewer than 100 staff or an annual operating budget below \$5 million. Organizations also had to be at least three years old and operational at the time of recruitment. The final requirement created a deliberate survivor orientation in the sample, consistent with prior nonprofit-resilience research (Searing, Wiley, and

Young 2021). Paper 3 uses this feature to examine the condition of organizations that remained open. I identified organizations through ProPublica’s Nonprofit Explorer, state nonprofit-association lists, county directories, and targeted web searches. Participants were senior organizational leaders, most often executive directors, chief executives, or founders. These leaders held primary responsibility for maintaining operations under disruption.

2.3. Data Collection

The county panel was assembled from public administrative data. For each of the three non-overlapping American Community Survey (ACS) five-year waves (2006–2010, 2012–2016, and 2018–2022), I constructed a multidimensional Social Capital Index following Kyne, Aldrich, and Kyei (2026). The index included bonding, bridging, and linking subindices and a composite score. Indicators came from the ACS and the National Neighborhood Data Archive (NaNDA). I linked each county-period to the FEMA major-disaster declarations occurring during the same five-year window. The resulting balanced panel contained 9,399 county-period observations.

I used Claude Code (Anthropic 2026b) to generate the R scripts used to assemble the panel. Before generating these scripts, I specified the data sources and vintages, panel structure, county exclusions, and indicator definitions. I also established the normalization and aggregation rules from Kyne, Aldrich, and Kyei’s (2026) methodology. I treated the resulting panel as preliminary until I had finished validating the results. I compared the indicators and subindices with the published methods, statistical code, and data dictionary. I also confirmed that all 3,133 units appeared in each wave and conducted exploratory checks before estimating the final models. Every deviation from the source methodology was a decision that I made, and because the entire pipeline is scripted, the panel can be regenerated from the raw sources and audited step

by step. This workflow used only public administrative data. No human-subjects material was processed with AI tools in this component of the study.

The interview and survey data were collected in two phases between December 2025 and July 2026. Leaders were invited by email to complete a 45- to 60-minute semi-structured interview¹, a roughly 10-minute Qualtrics survey, or both. These options for participation were intended to accommodate differences in organizational capacity. The interview protocol covered threat exposure and response, internal capacity, planning practices, financial condition, staff and leadership strain, community relationships, and leaders' definitions of resilience. The survey collected standardized information about organizational characteristics, disruption history, risk perception, planning practices and barriers, and support needs. Several structured interview questions mirrored survey items. This allowed comparable responses to be coded from interviews when leaders did not complete the separate survey. Phase 1 produced 20 interviews and 26 surveys. It also revealed modest response rates and several topics that the original protocol did not fully capture. These included leadership biography, board dynamics, and differences between direct-service and intermediary organizations. I revised the interview protocol and codebook before beginning Phase 2. The second phase added 30 interviews and 25 surveys and rebalanced outreach across the South, West, Northeast, and Midwest (CDC/NCHS 2024). In total, I contacted 421 organizations, and 80 participated. The participating

¹ Interviews were conducted over Zoom or Microsoft Teams, depending on participants' preferences. Interviews conducted over Microsoft Teams were transcribed using the platform's built-in automatic transcription tool, and I reviewed and corrected each auto-generated transcript against the recording; interviews conducted over Zoom were transcribed by hand by me. I created a master key linking participant names to pseudonyms, which was stored separately from all research data in a secure, password-protected file in my Northeastern Microsoft OneDrive. All transcripts were de-identified before analysis; this was especially important because the analysis used Claude (Anthropic 2026a), under specific safeguards described in Section 2.5.

organizations were located in 62 counties across 35 states and the District of Columbia. The study produced 51 survey responses and 50 interviews, with 21 organizations completing both instruments. The overall response rate was 19 percent, as shown in Table 1.

Table 1. Participant Response Rates

Region	Contacted	Participated	Response Rate
South	117	38	33%
West	109	22	20%
Northeast	108	11	10%
Midwest	87	9	10%
Total	421	80	19%

2.4. Data Analysis

2.4.1. County-Level Analysis

The county analysis used an equivalence framework to distinguish a precise null result from one produced by insufficient statistical power. After reviewing preliminary model results, I preregistered the final analysis plan before estimating and interpreting the final models. The preregistration fixed the primary specification, model hierarchy, effect-size threshold, and multiple-comparison rules. This reduced analytic flexibility across the final analyses (Simmons, Nelson, and Simonsohn 2011; Nosek et al. 2018). I defined 0.10 standard deviations as the smallest substantively meaningful effect. I assessed whether confidence intervals fell entirely within the corresponding positive and negative 0.10-standard-deviation bounds. I also reported minimum detectable effects to document the sensitivity of each design (Lakens 2017). The analysis estimated the relationship between FEMA-declared disaster exposure and county social

capital using county and wave fixed effects, first differences, and a difference-in-differences contrast following coarsened exact matching. All county-level analyses were conducted in R, version 4.4.3 (R Core Team 2025).

2.4.2. Qualitative Analysis

I manually coded the de-identified transcripts in ATLAS.ti using an abductive strategy (Timmermans and Tavory 2012). I began with a coding frame drawn from organizational-resilience research and used the Framework Method to compare cases and themes systematically (Gale et al. 2013). I revised the frame when recurring evidence did not fit the original categories. I then applied the final unified codebook across the full interview corpus.

Paper 2 analyzes the interviews at the level of threat-response episodes. I identified 326 episodes across the 50 organizations. Each episode represents one organization's encounter with a threat and its corresponding response. Within each episode, I identified capacities that the organization built, replenished, activated, or reconfigured to continue its mission. I treated these actions as capacity investments and assigned them to 33 indicators across six domains: financial, technological, social, human capital, operational, and planning. I also coded whether each investment took the form of a resource or process and whether it was already in place or developed in response to the threat.

Paper 3 analyzes the same interviews at the organizational level. I classified each organization as thriving, recovering, in strained continuity, or in depleted continuity. The rubric treated financial condition and organizational capacity as separate dimensions. Organizational capacity included staffing and operational infrastructure. I coded trajectory as improving, stable, or worsening separately from current condition. After assigning the condition classifications, I

conducted three focused reviews of all 50 transcripts. The first examined whether relationships produced concrete support, including funding, volunteers, shared services, and in-kind assistance. The second examined staffing conditions and support for staff well-being. The third assessed whether organizations had time to recover between disruptions. I completed these reviews without consulting the condition classifications.

Because one researcher completed the coding, I do not report intercoder reliability statistics. Coding consistency rests on repeated reviews of the full corpus, clearly defined rules, and line-by-line verification of every retained code against its supporting transcript evidence. Claude (Anthropic 2026a) played a bounded, preliminary role in the qualitative analysis. It surfaced candidate patterns, suggested possible codes, and retrieved relevant passages from de-identified transcripts. I treated these outputs as leads for further review. Every retained code and pattern was evaluated during the manual ATLAS.ti analysis and verified against its supporting evidence. Section 2.6 explains the methodological rationale and documentation procedures governing this use.

2.4.3. Survey Analysis

The survey component was exploratory. I summarized the full sample of 51 responses descriptively. Paper 3 uses one survey item to compare self-reported changes in organizational capacity with the interview-based condition classifications. Twenty-one organizations completed both instruments, and 20 answered the relevant survey item. The small paired sample did not support inferential analysis, so the comparison is presented as a limited descriptive check.

2.5. Ethical Considerations

The interview and survey data were collected under Northeastern University IRB approval (#25-10-44). Participation was voluntary, and interview participants consented to recording. Because a CBO can be identified through its mission and location, de-identification extended beyond personal and organizational names. Organizations are described in the manuscript only by broad region and service type. I reviewed each quotation for details that could identify a participant or organization. Research data are stored in a password-protected folder in my Northeastern University OneDrive account. The master key linking names to study identifiers is stored separately. Identifiable files will be deleted within two years of data collection, following the IRB-approved retention schedule.

AI-assisted work involving human-subjects data followed Northeastern University's AI Review Committee guidelines. Those guidelines require the use of university-approved tools operating under a university agreement. They also prohibit entering identifiable or confidential human-subjects' data into AI systems. Only de-identified transcripts and survey data were entered into Claude through Northeastern's institutional license. Participant names, organization names, recordings, consent records, and the master identification key were never entered into the system.

2.6. AI in the Research Process

Large language models are changing research practice and organizational life in consequential ways. Their adoption raises methodological and ethical questions that warrant sociological attention. As such, I approach these tools cautiously and critically. I have serious concerns about the pace of their adoption, weak regulation, and the broader societal, labor, and environmental impacts. Yet these tools are rapidly becoming a large part of the research

landscape, and refusing to engage with them would make me less equipped to evaluate their capabilities, critique their limitations, or use them responsibly. As a researcher who studies how organizations build capacity to respond to emerging threats and opportunities, I considered it important to understand how these tools can be leveraged appropriately, transparently, and ethically in both quantitative and qualitative research. As Abramson et al. (2026:54) stated, “Computational literacy matters. Just as quantitative and qualitative skills are both vital in a multi-method field like sociology, awareness of computational tools is part of engaging with the present and future of social inquiry.”

An emergent sociological methods literature is beginning to assess these tools. Some studies map the use of AI across computational, qualitative, and experimental research (Bail 2024; Davidson 2024) or evaluate their performance in qualitative coding (Than et al. 2025). Others document their entry into the everyday work of research and writing (Wang 2025) and explore how AI use can be integrated as a series of methodological choices that run through the lifecycle of a study (Abramson et al. 2026).

In this dissertation, I used Claude and Claude Code (Anthropic 2026a, 2026b) to generate scripts for public-dataset construction, flag candidate codes and patterns in de-identified interview transcripts (guided by coding rubrics I had established in advance), produce exploratory visualizations, and assist with figure generation. I leveraged AI in my research process while also keeping the research design, data-protection decisions, coding judgments, statistical verification, and interpretation under my control. The methodological literature informed which tasks I delegated to AI and which I retained (Than et al. 2025; Abramson et al. 2026). I limited AI assistance to tasks whose outputs I could easily verify and I retain ownership and responsibility for final coding decisions, interpretation, and theoretical development.

Within the typology of qualitative-computational engagement that Abramson et al. (2026) proposed, my workflow combined *streamlining* with *scaling up*. This means that scripted pipelines streamlined the computational work, which allowed me to maintain a repository that managed my qualitative and quantitative data in file formats that were easily readable alongside the R scripts that generated them. This infrastructure also scaled up what I, as a single researcher, was able to manage systematically. The workflow became *hybrid* at the points where I compared patterns developed through hand coding with structured quantitative analyses of the episode-level dataset.

At the same time, using these tools did not substitute for my own quantitative training or responsibility for the analysis. I have prior coursework in quantitative methods and R-based data analysis, including Analyzing Complex Digital Data and Introduction to Computational Statistics in R at Northeastern University, and training in data science and text analysis in R through the University of Michigan's ICPSR Summer Program. These experiences shape how I review generated code, check outputs, interpret results, and decide which computational tasks could be appropriately delegated to an AI tool.

A separate methodological debate important to mention here, especially in the context of papers 2 and 3, is whether generative AI is compatible with reflexive qualitative research. A collective statement signed by hundreds of qualitative researchers rejects its use in reflexive analysis (Jowsey et al. 2025). The authors argue that this form of analysis depends on the subjectivity and position of the human researcher. They also raise social and environmental justice concerns. Mendoza and Quilantang (2026) take a different position. They argue that technological mediation can be compatible with reflexive practice when its use is contextual, transparent, and documented.

My own experience reinforces the importance of distinguishing interpretive analysis from the tasks that support it. I maintained repeated and close engagement with the transcripts in ATLAS.ti and was responsible for producing the initial and primary categories, hunches, and analytic foundations of this study. No AI-assisted process offered a substitute for that work or for getting familiar with the qualitative data. AI was useful for organizing, retrieving, and checking material surrounding the interpretive analysis. Its usefulness depended on clearly defined tasks, documentation, and verification.

Following emerging disclosure guidance, I documented the tool used, the task assigned, the materials it accessed, the output it produced, and the human review that followed (Jones 2025). Two practices structured my use of AI. The first was organizational. Agentic systems such as Claude Code can generate scripts, figures, memos, and analyses faster than a single researcher can review them. This speed creates a risk of losing track of what is being created. To maintain oversight, I kept a version-controlled project repository and knowledge base on my computer as the working directory for Claude Code. The repository contained codebooks, analytic memos, figure- and table-generation scripts, and analysis outputs. This structure kept AI-accessible inputs and retained outputs in one documented place. It also allowed each new session to work from the same organized project materials. I retained and tracked every AI-assisted output used in the dissertation. My logs recorded what I asked the system to do, which materials it accessed, what it produced, how I checked the output, and what I accepted, revised, or discarded. Only de-identified interview and survey data were placed in the AI-accessible workspace. Recordings, identifiable transcripts, contact information, consent records, and the master identification key were stored separately and were not available to Claude. The second practice was supervisory. I treated every AI output as preliminary. I delegated clearly defined

tasks and checked each candidate code, analysis, and draft figure against the underlying data before using it. This review required me to examine what the model missed, where it overreached, and whether the evidence supported its conclusions.

AI also supported two secondary research tasks. While coding the interviews, I recorded voice memos containing immediate reactions, possible patterns, and questions about the data. Claude organized these memos into analytic notes, which I reviewed before use. During manuscript drafting, I requested feedback on clarity, whether concepts were defined before use, and whether a section's structure supported its argument. I retained responsibility for the content and wording of the final manuscript.

My use of AI-assisted literature-review tools was more limited. I used Elicit to identify potentially relevant publications released after my last comprehensive literature review. I located, read, and evaluated each original publication before citing it or incorporating its findings. Across all uses, AI functioned as a supervised methodological tool. Its value depended on clear task boundaries, protection of confidential data, documentation, and independent verification.

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Paper 1: Stable Ground: Recurrent Disaster Exposure and County-Level Social Capital in the United States

Abstract

Disaster scholarship treats social capital as a central community resource that shapes preparedness, response, and recovery (Norris et al. 2008; Aldrich 2012; Aldrich and Meyer 2015). However, less is known about whether disasters build, erode, or reorganize the social capital of the communities they strike over time. This paper tests that question using a preregistered national panel of 3,133 U.S. counties observed across three non-overlapping American Community Survey (ACS) five-year waves: 2006–2010, 2012–2016, and 2018–2022. I link Federal Emergency Management Agency (FEMA)-declared disaster exposure to a multidimensional Social Capital Index (SoCI), following Kyne, Aldrich, and Kyei’s (2026) updated methodology. The index includes bonding, bridging, and linking subindices and a composite score constructed from publicly available ACS indicators (U.S. Census Bureau 2022) and the National Neighborhood Data Archive (NaNDA) Civic, Social, and Religious Organizations dataset (Melendez et al. 2024).

Because ACS five-year estimates average conditions across a five-year period rather than measuring counties at a single point in time, I treat each wave as a five-year county-period. I then compare FEMA declarations occurring within each five-year window to the average social-capital conditions measured over that same window. Across three preregistered identification strategies (county and wave fixed effects, first differences, and a coarsened exact matched difference-in-differences contrast), FEMA-declared disaster exposure is not associated with

substantively meaningful change in composite social capital. The primary within-county estimate is near zero ($\beta = -0.00039$; 95% CI $[-0.0010, 0.0002]$; $p = .213$), corresponds to roughly -0.01 standard deviations, and is precise enough to detect effects well below the 0.10 standard-deviation threshold I treat as meaningful. Before matching, the disaster-prone counties appear to have lower social capital. However, after highly exposed counties are compared with baseline-similar peers in the same broad region, that gap disappears. Community social capital at the county-index level therefore appears less like a reflexive response to disaster than a stable feature of county-level social structure.

Keywords: social capital; disaster exposure; FEMA declarations; Social Capital Index; community resilience

1. Introduction

Within disaster scholarship, social capital has become central to the study of community resilience. Communities with strong bonding, bridging, and linking ties are often better positioned to share information, coordinate action, access outside resources, and recover after major disruptions (Aldrich 2012; Aldrich and Meyer 2015). In this literature, social capital is understood as a causal resource that shapes how communities prepare for, respond to, recover from, and adapt after disasters. Yet this research has paid less attention to social capital as a possible outcome of disaster exposure. If bonding, bridging, and linking ties shape how communities withstand disasters, do repeated disasters also alter those ties over time?

This question is relevant for both theory and policy. If disasters build or erode social capital, then social capital is not only a pre-existing resource that supports resilience but also a measurable resource that disasters may change over time. But if social capital remains stable under recurrent exposure, then differences between disaster-prone and less-exposed counties

may reflect stable historical, demographic, institutional, and geographic conditions rather than the cumulative effects of disasters themselves. This distinction is especially important in the United States, where communities face repeated federally declared events and where disaster-prone places are not randomly distributed across the social landscape.

Existing research suggests that disasters can affect local social life. However, the studies are hard to compare because they measure different outcomes at different scales. U.S. county-level studies primarily measure social capital through organizational infrastructure (i.e., associations, nonprofits, or counts of bonding and bridging social-capital organizations) and generally find modest and condition-dependent effects (Wang and Ganapati 2018; Smiley, Howell, and Elliott 2018; Michael et al. 2022). International and survey-based work likewise suggests that disasters do not move social capital in a uniform direction. Some studies find increases in cohesion or trust following disasters (Toya and Skidmore 2014; Calo-Blanco et al. 2017), while others find small, temporary, negative, or type-specific effects (Albrecht 2018; Schilpzand 2023; Li and McNaught 2026). These findings motivate a broader test in this paper of whether recurrent disaster exposure moves multidimensional community social capital at the U.S. county scale.

In this paper, I assemble a balanced three-wave national panel of 3,133 counties and link FEMA major disaster declarations to a multidimensional Social Capital Index (SoCI) constructed using the indicator selection, normalization, and subindex aggregation procedure developed by Kyne, Aldrich, and Kyei (2026). The index includes bonding, bridging, linking, and composite social capital. Bonding social capital is defined as ties among close and similar people (family, friends, neighbors) that support mutual aid within groups; bridging social capital includes the ties that cut across social boundaries such as race, class, or religious affiliation and connect otherwise

separate groups; and linking social capital involves the vertical ties that connect residents to institutions, public agencies, and people in positions of power (Putnam 2000; Szreter and Woolcock 2004; Aldrich and Meyer 2015).

This paper takes a macro, community-level approach in the tradition of Putnam (2000). It treats social capital as a property of places measured through aggregate indicators of networks and civic infrastructure. This approach differs from micro, individual-level accounts that treat social capital as resources accessed through personal ties (Bourdieu 1986; Lin 2001). Each wave corresponds to a non-overlapping ACS five-year window (2006–2010, 2012–2016, and 2018–2022). As such, I interpret each observation as a five-year county-period, not a point-in-time measure. The primary analysis estimates the association between FEMA-declared exposure during each window and average county social-capital conditions over the same period.

The analysis plan was preregistered before the final models were run, limiting further analytic flexibility (Simmons, Nelson, and Simonsohn 2011; Nosek et al. 2018). I defined 0.10 standard deviations as the smallest meaningful association and evaluated each confidence interval against the corresponding ± 0.10 bounds (Lakens 2017). The primary estimate is near zero, and its confidence interval falls within those bounds. Thus, FEMA-declared disaster exposure is not associated with meaningful change in composite county social capital or consistent shifts in the bonding, bridging, and linking subindices. Disaster-prone counties have lower social capital in cross-section. This gap is no longer statistically distinguishable from zero when highly exposed counties are matched to baseline-similar peers in the same region. This pattern is consistent with preexisting county differences, not disaster-driven change. At the scale captured by the SoCI, community social capital is stable ground.

2. Background

2.1. Social Capital Shapes Disaster Outcomes

Most disaster research treats social capital as something communities bring into a disaster. Social capital is typically treated as a pre-existing resource that helps communities prepare for, respond to, and recover from shocks. Bonding ties can support mutual aid and emotional support; bridging ties can connect groups across social boundaries; and linking ties can facilitate access to institutions, public agencies, and external resources (Aldrich 2012; Aldrich and Meyer 2015). This literature has been central to disaster sociology and resilience research because it explains why communities with similar physical damage can experience very different recovery trajectories.

The same literature also recognizes that social capital is not universally protective. Bonding ties can be exclusionary, linking ties can be unevenly distributed, and the bridging resources embedded in networks may help some groups recover while leaving others outside main support channels (Aldrich 2012; Smiley, Howell, and Elliott 2018). The question is therefore not whether social capital matters for disasters. It clearly does. The more open question is whether disasters, especially repeated disasters, change the social ties and institutional connections that communities carry forward.

2.2. Organizational Infrastructure as Social Capital

The U.S. studies most directly comparable to this paper are longitudinal county-level analyses that ask whether disasters change social capital, but they operationalize social capital through organizational infrastructure rather than through a multidimensional index. Wang and Ganapati (2018) analyze 182 Gulf Coast counties before and after Hurricane Katrina, measuring social capital through associations and nonprofit

organizations. They find that Katrina temporarily slowed the growth of social capital, although growth later recovered and counties receiving more federal assistance experienced stronger post-Katrina social-capital growth.

Smiley, Howell, and Elliott (2018) extend this organizational approach across U.S. counties from 1998 to 2015. They examine how natural-hazard property damages correlate with subsequent changes in poverty and in counts of for-profit, bonding, and bridging social-capital organizations. Building on Aldrich's (2012) argument that social capital can be double-edged, Smiley et al. (2018) show that post-hazard organizational growth is not necessarily protective for the wider community. Organizations built around shared membership, faith, recreation, or social affiliation can help members mobilize support, but leave those outside such networks with weaker access to recovery resources. In their analysis, poverty rises most where these bonding organizations increase after hazard damages. In this account, bonding organizations may provide valuable communal insurance to in-group members and also inadvertently marginalize residents with less access.

Michael et al. (2022) similarly examine annual county-level growth in social-capital organizations from 2000 to 2014. They find that a greater number of disaster months is associated with more social-capital organizations one year later. The association varies by disaster scale and pre-disaster organizational stock. Following smaller-scale disasters, growth is greater in counties that already have more social-capital organizations. This pattern suggests that disaster-related growth can widen existing differences across counties.

Together, these studies show that disasters can reshape the local associational infrastructure often used to measure community social capital. However, they do not fully investigate if disasters reshape community social capital as a broader multidimensional county-

level construct. A county can gain organizations without increasing cross-group trust, institutional access, or civic integration; additionally, a county can maintain a stable social-capital score even while particular organizations are strained or unevenly distributed. Existing organizational-count studies therefore motivate the question asked in this paper without resolving it.

2.3. Disaster Effects on Social Capital Vary by Context and Dimension

Studies that investigate disasters as drivers of social capital change find a more complex pattern than simple growth or erosion. Effects instead vary with the scale of analysis, the type and severity of the disaster, and the dimension of social capital being measured. Toya and Skidmore (2014) use cross-national and panel data to ask whether different types of natural disasters (storms, floods, earthquakes, landslides, and volcanic eruptions) have different impacts on societal trust. They find a positive association that is driven by storms. Storm frequency is strongly associated with higher generalized trust across specifications, which they attribute to storms striking broad cross-sections of society and thereby demanding collective preparation and response. Floods, whose burdens fall unevenly on low-lying and poorer areas, show a negative association in cross-section that is not robust, and the remaining disaster types show no consistent relationship. Calo-Blanco et al. (2017), examining spatial and temporal variation in earthquake exposure across Chile, find positive effects on a broad set of social-cohesion indicators (e.g., trust, life satisfaction, volunteering, charitable giving, and electoral participation, alongside lower crime). Essentially, cohesion rises in affected areas after a major earthquake and then slowly erodes as time since the last event grows.

Research that distinguishes disaster severity and types of social capital reveals more specific patterns. Albrecht (2018) analyzes 12 European disasters using European Social Survey

data and finds no consistent change in social trust across cases. Declines in social capital occur most often after severe events. Schilpzand's (2023) international study, of 150,000 individuals from 82 countries, finds higher ingroup trust following disasters. Evidence of lower outgroup trust is weaker and inconsistent. Longitudinal research in Australia associates repeated climate-related disasters with declines in bonding social capital and increases in bridging or linking ties (Li and McNaught 2026). The authors interpret this shift as a move toward support beyond close networks.

Three outcomes remain possible: disasters can build social capital, erode it, or leave it largely unchanged at the county level. Growth in social capital can follow from mutual aid, shared identity, and collective problem solving. Erosion can result from displacement, organizational exhaustion, institutional damage, or widening inequality. Disasters could also leave county-level social capital largely unchanged if social capital at that scale is rooted in stable demographic, institutional, and historical features of place. This paper investigates the extent to which recurrent disaster exposure produces measurable change in county-level social capital.

2.4. Rationale for a Multidimensional Social Capital Index

This paper addresses this gap by testing whether recurrent FEMA-declared disaster exposure changes a multidimensional county-level Social Capital Index (SoCI) in the United States. I use SoCI because the object of interest is not only what disasters do to formally counted organizations, but what disasters do to the broader social-capital functioning of the communities in which organizations operate. Community-based organizations (CBOs) are one institutional expression of local social capital. CBOs create environments where residents interact, build trust, form relationships, mobilize resources, and coordinate collective action. Yet the organizations

most central to disaster response and community support are often small, grassroots, volunteer-run, or newly emergent. These are precisely the kinds of organizations that national administrative datasets are least likely to capture consistently.

SoCI does not solve that problem by measuring small organizations directly. It instead shifts the empirical question: If the smallest organizations cannot be observed reliably at national scale, can one observe whether disaster exposure changes the broader county-level social-capital environment in which they provide their services? By measuring bonding, bridging, linking, and composite social capital, SoCI provides a national picture of whether disasters alter the community relational infrastructure that organizations and residents depend on.

Kyne, Aldrich, and Kyei's (2026) comparison of 2010 and 2022 SoCI scores shows that social capital is stable nationally even as individual counties change over time. Recurrent disaster exposure is one possible source of that change. Disasters can strain organizations, alter population composition, mobilize civic ties, and reshape access to institutions. This paper tests whether FEMA-declared disaster exposure explains within-county change in SoCI. It also examines whether the lower social capital observed in disaster-prone counties reflects preexisting county differences instead of disaster-driven erosion.

Kyne, Aldrich, and Kyei (2026) also validate the updated SoCI by using it to predict disaster outcomes. Their empirical analysis treats social capital as a community resource, finding that counties with higher SoCI scores are associated with lower disaster damages and injuries, suggesting that social capital helps mitigate the consequences of hazard exposure. This paper shifts the focus from how social capital protects communities from disaster losses to how recurrent disaster exposure changes the social-capital structure of counties over time. These are complementary but distinct relationships. Social capital may reduce disaster impacts without

being substantially changed by repeated exposure. Treating SoCI as the outcome therefore tests whether county social capital changes measurably as disaster exposure accumulates. It also helps distinguish changes associated with exposure from broader county-level trends unfolding over the same period.

3. Methods

3.1. Data and Sample

I constructed a balanced three-wave panel of 3,133 U.S. counties and county-equivalent units, yielding 9,399 county-period observations. In this paper, I refer to these units as counties throughout. The panel combines social-capital indicators from the National Neighborhood Data Archive (NaNDA) and the American Community Survey (ACS), disaster declarations from the Federal Emergency Management Agency (FEMA), and county demographic context from the ACS.

The three waves correspond to three non-overlapping ACS five-year windows: 2006–2010, 2012–2016, and 2018–2022. I labeled these windows by their midpoint years, 2008, 2014, and 2020, only to organize the panel. Each wave in the study represents average county characteristics over the full five-year ACS period, not a point-in-time observation. The windows are deliberately non-overlapping because adjacent rolling ACS five-year products include some of the same years, so consecutive waves would partly reflect the same underlying data.

Following the panel construction protocol, I excluded Connecticut because of its 2022 county-equivalent reorganization. I also excluded U.S. territories and reconciled county-code changes where clean crosswalks were available. I dropped the Valdez-Cordova, Alaska, split geographies. Valdez-Cordova Census Area appears in the earlier data but was later divided into new county-equivalent units, including Chugach and Copper River. Because this change is a split

rather than a one-to-one rename, I was unable to map the earlier unit cleanly onto a single later unit. By dropping these geographies, I ensured that each county-equivalent unit in the panel refers to a consistent place across all three waves (see Appendix Table 2).

I assembled the panel with Claude Code (Anthropic 2026), an AI-assisted coding tool, under parameters I specified in advance. Before any code was generated, I fixed the data sources and vintages (the three non-overlapping ACS five-year windows, the corresponding NaNDA organizational data, and FEMA major disaster declarations), the panel structure and county exclusions, the indicator definitions, and the normalization and aggregation rules following Kyne, Aldrich, and Kyei (2026). Claude Code then generated and executed the R scripts that retrieved the public data and assembled the panel according to those specifications. I treated the resulting datasets as preliminary output, not a completed dataset. I verified the constructed indicators and subindices against the published methodology and the original authors' statistical code and data dictionary (Kyne, Aldrich, and Kyei 2026), confirmed the panel structure (3,133 counties observed in each of the three waves), and reviewed the assembled panel through exploratory checks before any final model was run. Every deviation from the source methodology was a decision I made and recorded, and because the entire pipeline is scripted, the panel can be regenerated from the raw sources and audited step by step. This workflow involved only public administrative data; no human-subjects material was processed with AI tools. All panel construction and analyses were conducted in R (version 4.4.3; R Core Team 2025); all regression models were estimated with the *fixest* package (Bergé, Butts, and McDermott 2026).

3.2. Social-Capital Measurement

County-level social capital was measured using a Social Capital Index (SoCI) constructed from indicators drawn from the American Community Survey (ACS) and the

National Neighborhood Data Archive (NaNDA), following Kyne, Aldrich, and Kyei's (2026) updated methodology. I adapted the revised index for a three-wave panel by applying the same measurement logic across the 2006–2010, 2012–2016, and 2018–2022 windows. Organizational indicators were drawn from the NaNDA Civic, Social, and Religious Organizations dataset (Melendez et al. 2024). I use tract-level counts on 2010 Census tract boundaries measured in 2010, 2014, and 2021, matched to the 2006–2010, 2012–2016, and 2018–2022 waves respectively, and aggregated them to counties.

The SoCI is organized into three theoretically distinct subindices and a composite score. The bonding subindex (BONDG) draws on ACS-derived indicators of demographic similarity, socioeconomic equality, language competency, and age structure. The bridging subindex (BRIDG) uses NaNDA-derived measures of associational infrastructure, including religious, civic, veterans, and youth organizations measured both per capita and by geographic density. The linking subindex (LINKG) combines ACS-derived indicators of political and government linkage with NaNDA-derived measures of organizational employment linkage. The composite score (SOCIX) is the equal-weight mean of the three subindices (see Appendix Table 1).

The bonding indicators in particular require closer examination and explanation. Measuring bonding social capital through county-level demographic similarity and socioeconomic equality assumes that similarity supports within-group ties, yet homogeneity measured at the county scale can mask segregation within counties, and the presence of associational resources does not establish who can access them. I retained the indicator set for two reasons. First, using the validated SoCI construction preserves comparability with prior findings based on the same measure (Kyne, Aldrich, and Kyei

2026). This allows the null results reported here to be interpreted in relation to that earlier work. Second, the analysis examines within-county change over time. Limitations that remain stable within counties do not, on their own, create the appearance of change. Retaining the bonding indicators is therefore an analytic choice. I do not treat them as complete measures of bonding social capital.

To preserve comparability across the three waves, I evaluated the communication-capacity indicator (COMMC) explicitly. COMMC was retained in the primary BONDG construction to maintain alignment with Kyne, Aldrich, and Kyei's (2026) revised SoCI indicator set. However, because the underlying ACS B25043 communication-access item changes between 2018 and 2019, shifting from telephone service availability to computer/internet access, I also report a sensitivity specification that excludes COMMC from BONDG. I then normalized the indicators across the pooled three-wave panel so that scores carry the same relative meaning over time. Finally, I computed each subindex as the row mean of its component indicators and constructed the composite SoCI score as the equal-weight mean of the bonding, bridging, and linking subindices. This approach prevents subindices with more component indicators from receiving greater weight in the composite measure.

Table 1. Social Capital Measures and Sources

Measure	Meaning	Source
Bonding (BONDG)	Demographic similarity and socioeconomic equality	ACS

Bridging (BRIDG)	Associational infrastructure connecting residents across groups	NaNDA
Linking (LINKG)	Connections to public institutions and organizational employment structures	ACS and NaNDA
Composite (SOCIX)	Equal-weight mean of BONDG, BRIDG, and LINKG	Constructed from the three sub-indices

Note. Adapted from Kyne, Aldrich, and Kyei’s (2026) updated SoCI methodology.

3.3. FEMA-Declared Disaster Exposure

Disaster exposure was measured from Federal Emergency Management Agency (FEMA) Disaster Declarations Summaries data (2026), restricted to major disaster declarations for hazard events such as hurricanes, floods, severe storms, wildfires, tornadoes, and winter storms, and excluding COVID-19 and coronavirus-related events. Because the FEMA data can list the same disaster more than once for a county when multiple assistance programs are involved, I collapsed records to one observation per county and disaster number. For each county-period, the primary exposure measure is the count of unique FEMA major disaster declarations affecting that county within the corresponding ACS five-year window: 2006–2010, 2012–2016, or 2018–2022.

I refer to this measure as FEMA-declared disaster exposure because a declaration reflects both hazard impact and federal administrative recognition. This distinction is analytically important. A declaration formally recognizes an event and makes designated areas eligible for federal disaster assistance. It does not directly measure physical hazard exposure, property damage, mortality, displacement, or local disruption. The analysis

therefore examines whether changes in FEMA-declared disaster exposure are associated with changes in average county social-capital conditions over the same five-year period (Figure 1).

Change in FEMA-Declared Disaster Exposure Across ACS Windows

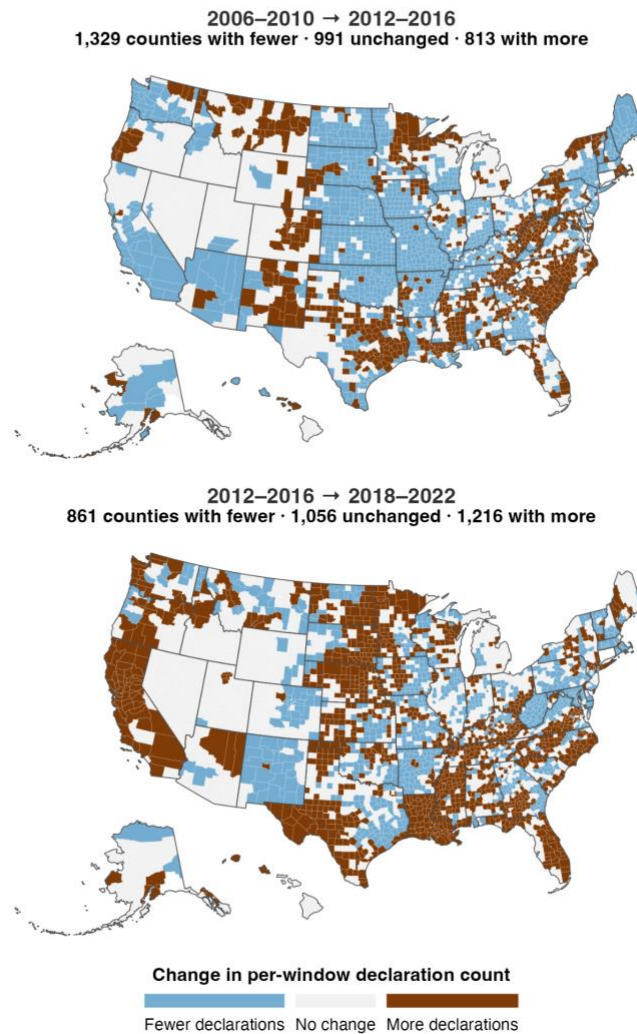


Figure 1. Change in FEMA major disaster declaration counts between consecutive five-year ACS windows. The panel headers show the number of counties in each category. Counties move into and out of higher-exposure periods instead of rising steadily over time; this within-county variation identifies the fixed-effects models. $N = 3,133$ counties and county-equivalent units, excluding Connecticut and U.S. territories. Major disaster declarations only; COVID-19 declarations excluded.

3.4. Estimating the Relationship Between Disaster Exposure and Social Capital

This paper tests whether FEMA-declared disaster exposure is associated with within-county change in social capital. The preregistered primary specification estimates the following model:

$$SOCIX_{it} = \beta \log(1 + DuringCount_{it}) + \alpha_i + \tau_t + \epsilon_{it}$$

In this model, $SOCIX_{it}$ is the composite social-capital score for county i during wave t . The exposure term is the logged count of FEMA declarations in the corresponding five-year ACS window. County fixed effects (α_i) account for stable differences across counties, and wave fixed effects (τ_t) account for national shifts shared across the three time periods. The coefficient β estimates the within-county association between changes in FEMA-declared exposure and changes in composite social capital, and ϵ_{it} is the error term.

County fixed effects account for stable differences across counties, including region, long-run civic culture, rurality, persistent geographic vulnerability, and baseline social capital. Wave fixed effects account for national changes shared by all counties during each ACS period. The disaster-exposure coefficient captures the association between changes in FEMA-declared exposure and changes in social capital within the same county. The model asks whether a county's social capital changes as its disaster exposure changes, after accounting for national shifts across waves.

Unobserved county conditions that change over time and relate to both disaster exposure and social capital could still bias the estimate (Imai and Kim 2019, 2021). Spatially correlated errors present a separate issue. Nearby counties can experience shared shocks, creating

correlation in their regression errors. I therefore used Conley (1999) spatial standard errors, which allow correlation among counties within 100 km (see also Kelejian and Prucha 2007). I also report state-clustered standard errors as a robustness check, allowing correlation among counties within the same state (Bertrand, Duflo, and Mullainathan 2004; Cameron and Miller 2015).

The primary specification relates FEMA-declared exposure within each five-year ACS window to composite social capital (SoCI) measured over that same period. Secondary analyses examine alternative timing windows, the bonding, bridging, and linking subindices, and hazard-specific exposure.

The five-year design creates a timing concern. Declarations near the end of a window contribute little post-event time to that window's pooled ACS estimate. Effects that develop over several years could therefore appear in the next wave. I examined this possibility in three ways. First, I added exposure during the preceding five years. The lookback windows (2001–2005, 2007–2011, and 2013–2017) capture declarations before each ACS period, including declarations in the late years of the previous window and in the intervening years of 2011 and 2017. This specification allows delayed associations to appear in the next wave. Second, I separated declarations from the first two years of each window from those in the final three years. Early-window declarations provide more time for an association to appear in the pooled ACS estimate. Third, the matched analysis compares cumulative exposure from 2006 through 2022 with change in social capital from the 2008 baseline to 2020. This longer horizon reduces the influence of a declaration's exact timing within a window. Section 4.5 reports these checks.

I paired the fixed-effects model with two additional designs to assess whether the findings depend on a single approach. First, I estimated a first-difference model that relates changes in composite social capital to changes in FEMA-declared exposure across adjacent waves, with wave fixed effects. Differencing removes stable county characteristics without requiring county fixed effects. Second, I used coarsened exact matching to compare highly exposed counties with low-exposure counties that had similar baseline subindex scores and belonged to the same region. I used the CDC/NCHS four-region classification because it follows the Census regional structure and preserves enough comparison counties within each region (CDC/NCHS 2024). The preregistered difference-in-differences analysis compares change in composite social capital among highly exposed counties with change among their matched peers. I also estimated the fixed-effects model within the matched sample. This model serves as a continuity check on the within-county estimate. The matched difference-in-differences analysis remains the primary between-group contrast.

Each design addresses a different concern. The fixed-effects model removes stable county differences across the three available waves. The first-difference model makes change across adjacent waves explicit and is more sensitive to measurement error. The matched design balances observed baseline conditions and leaves unobserved differences unresolved. Similar results across the three designs provide stronger support for the interpretation than any one estimate alone.

3.5. Preregistration

I preregistered the final analysis plan after reviewing preliminary model results and before estimating and interpreting the final model set. The preregistration distinguished planned

analyses from exploratory ones and fixed the primary specification, the hierarchy of primary and secondary analyses, the effect-size threshold, the false-discovery-rate families, and the matched difference-in-differences average treatment effect on the treated (ATT). The matched ATT contrast had not been estimated before preregistration. Fixing these decisions limited subsequent analytic flexibility across plausible modeling choices (Simmons, Nelson, and Simonsohn 2011; Nosek et al. 2018). The full preregistered result set is reported in Appendix Table 3.

The preregistration also established the rules for interpreting the results. I evaluated subindex estimates using Benjamini–Hochberg false-discovery-rate adjustments (Benjamini and Hochberg 1995). I defined 0.10 standard deviations as the smallest meaningful effect (Lakens 2017; Lakens, Scheel, and Isager 2018). A confidence interval contained entirely within the corresponding ± 0.10 bounds supports the conclusion that any association is smaller than this threshold. The paper’s primary claim rests on the preregistered composite estimates from the county and wave fixed-effects model, the first-difference models, and the matched difference-in-differences analysis. Timing checks and subindex analyses remain exploratory. The paper’s central conclusions therefore rest on the preregistered composite results.

I report point estimates, confidence intervals, standardized effect sizes, and minimum detectable effects. Minimum detectable effects indicate the smallest association the design could detect under the stated assumptions (Bloom 1995). Together, these measures distinguish a precise null from an underpowered result.

4. Results

4.1. No Meaningful Association Between Disaster Exposure and Composite Social Capital

The primary fixed-effects model shows no evidence that FEMA-declared disaster exposure within the same five-year ACS window is associated with meaningful change in composite county social capital. After accounting for county and wave fixed effects, the estimated association between FEMA-declared exposure and SoCI is -0.00039 , with a 95 percent confidence interval of $[-0.0010, 0.0002]$ and a p-value of .213. Expressed in standardized terms, this association is approximately -0.01 standard deviations. The full set of preregistered composite estimates is reported in Table 2. It is therefore both statistically nonsignificant and substantively small.

The precision of the estimate is important for interpreting this null result. The primary fixed-effects design has a minimum detectable effect of 0.024 standard deviations, roughly one-quarter of the 0.10 standard-deviation effect that I define as meaningful. The absence of a significant association is therefore not simply a consequence of low statistical power. The model is sufficiently sensitive to detect effects well below the preregistered threshold of substantive importance. The confidence interval also falls within the preregistered equivalence band, supporting the interpretation that any average association between co-period FEMA-declared exposure and composite SoCI is smaller than this study defines as meaningful.

This is the paper's central empirical finding. Across the five-year ACS windows observed, recurrent FEMA-declared disaster exposure does not appear to measurably erode, build, or reorganize composite county social capital. The result points instead toward stability, where composite social capital is largely stable in the face of recurrent federally declared disaster exposure, at least at the spatial and temporal scale captured by this panel.

4.2. The Null Result Is Consistent Across Estimators

The same substantive conclusion holds across the two additional designs. The first-difference specification, which regresses change in composite social capital on change in FEMA-declared exposure across adjacent waves, returns a similarly precise null result. The estimate remains negative in direction, but it is small, statistically nonsignificant, and well below the preregistered threshold for substantive importance. The matched contrast also provides no evidence of a meaningful difference between highly exposed counties and baseline-similar comparison counties in the same region. The standardized average treatment effect is approximately -0.07 standard deviations, with a p -value of .257.

This convergence is important because the three designs rely on different assumptions. The fixed-effects model estimates within-county change while absorbing stable county characteristics. The first-difference model makes change across adjacent waves explicit. The matched contrast compares highly exposed counties with otherwise similar low-exposure counties within the same broad regional context. Despite these differences, all three approaches point to the same substantive conclusion, that recurrent FEMA-declared disaster exposure is not associated with meaningful change in composite county-level social capital. Table 2 summarizes the composite estimates across the primary fixed-effects model and the two triangulating analyses. The matched contrast, however, is less precise than the other two designs. Its minimum detectable effect of 0.178 standard deviations exceeds the preregistered 0.10-standard-deviation threshold, so it functions as a triangulating check rather than as an independent equivalence result.

Table 2. Composite SoCI Estimates Across Analyses

Analysis	Exposure term	Estimate (SE)	p	MDE (SD)
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County and wave fixed effects	log(1 + same-window declarations)	−0.00039 (0.00032)	.213	0.024
First difference	Change in log(1 + declarations)	−0.00043 (0.00027)	.120	0.047
Matched difference-in-differences	Top versus bottom cumulative-exposure tercile	−0.00152 (0.00134)	.257	0.178

Note. All analyses use composite SoCI in raw index units. The matched difference-in-differences estimate corresponds to approximately -0.07 standard deviations. MDE = minimum detectable effect in standard deviations.

4.3. The Exposure Gap Narrows After Matching

A simple comparison between high- and low-exposure counties tells a different story than the within-county models. In the final wave, counties in the highest cumulative-exposure tercile have substantially lower social capital than counties in the lowest exposure tercile. The difference is approximately -0.29 standard deviations, with a 95 percent confidence interval of $[-0.38, -0.20]$. On its own, this pattern could be read as evidence that repeated disaster exposure erodes social capital.

The matched analysis shows why this interpretation is incomplete. When highly exposed counties are compared with baseline-similar counties in the same broad region, the difference is no longer statistically distinguishable from zero. Counties with higher disaster exposure therefore appear to have lower social capital when compared with less-exposed counties at the same point in time. The cross-sectional gap is more consistent with selection on stable county characteristics than with detectable within-county erosion. This is the form of confounding that the within-county and matched designs are intended to address.

4.4. No Consistent Pattern Across Social Capital Subindices

Disaggregating the composite index into bonding, bridging, and linking social capital does not change the main finding of this paper (Table 3). The bonding and linking estimates are small and not statistically significant on their own. The bridging estimate is nominally significant before correction in the levels, during-only model ($\beta = -0.00039$, $p = .027$), but not after BH-FDR correction across the preregistered set of subindex tests ($q = .082$). Its standardized magnitude is also very small, approximately 0.016 standard deviations, and the association does not appear in the first-difference model or under the primary matched contrast. I therefore do not treat the bridging estimate as reliable evidence of a disaster effect.

Table 3. Subindex Estimates from the Same-Window Fixed-Effects Model

Subindex	Estimate (SE)	p	q
Bonding (BONDG)	−0.00091 (0.00080)	.256	.384
Bridging (BRIDG)	−0.00039 (0.00018)	.027	.082
Linking (LINKG)	−0.00002 (0.00031)	.951	.951

Note. Estimates are from county and wave fixed-effects models with $\log(1 + \text{during-window FEMA declaration count})$ as the exposure term. q -values are Benjamini–Hochberg false-discovery-rate adjustments calculated within the preregistered subindex family. Subindex definitions follow Table 1.

The direction of the bridging coefficient is still worth noting. The negative estimate suggests that more exposed county-periods may show a slight decline in the associational

infrastructure captured by the bridging subindex (the density of religious, civic, veterans, and youth organizations). But the coefficient is too small, too sensitive to multiple-comparison adjustment, and too dependent on a single estimator to support a firm claim. Thus, the result is interpreted as a descriptive irregularity rather than as evidence that FEMA-declared exposure erodes bridging social capital.

The linking result is also informative, though the expected direction is theoretically ambiguous. Major disaster declarations can create opportunities for linking social capital to increase by routing federal attention, public assistance, and administrative coordination toward affected counties. Wang and Ganapati's (2018) study of Hurricane Katrina, for example, finds that federal disaster assistance was associated with stronger post-Katrina social-capital growth, partly because assistance helped affected nonprofit organizations restore capacity and remain active in their communities. At the same time, disasters can also damage linking social capital when public response is slow, unequal, or difficult to access. Katrina again illustrates this where the disaster overwhelmed government capacity, and nonprofit organizations filled gaps when public agencies failed to respond immediately and efficiently. For that reason, the linking null should not be read as surprising, as if linking capital should necessarily increase after declarations. Rather, it suggests that these competing pathways do not aggregate into measurable movement in the county-level linking subindex over the five-year periods observed here.

4.5. Secondary and Sensitivity Analyses Leave the Main Finding Unchanged

Several secondary and sensitivity results are worth reporting. First, prior five-year exposure is marginally positively associated with composite social capital in a secondary levels

specification ($p = .052$). This direction is consistent with the “therapeutic community” literature, which documents temporary solidarity, mutual aid, and civic mobilization following crises, and with more recent evidence that social-capital organizations may grow after some disaster exposures (Fritz 1996 [1961]; Barton 1969; Wang and Ganapati 2018; Michael et al. 2022). However, this estimate addresses a secondary exposure window, and the statistical evidence is too weak to support a claim that disaster exposure builds county social capital.

Second, a first-difference specification that adds an indicator for counties newly exposed during a window yields a nominally significant coefficient for that indicator ($p \approx .019$), equivalent to roughly 0.04 standard deviations. The negative coefficient indicates that the change in composite social capital was approximately 0.04 standard deviations lower among counties newly exposed during the window than among counties that were not newly exposed during that window. The estimate may reflect a short-run adjustment following new exposure. Its magnitude remains below the preregistered 0.10-standard-deviation threshold for substantive importance, and the preregistered primary first-difference model is null. I therefore report this estimate as an additional robustness check.

The exploratory timing split described in Section 3.4 addresses whether declarations occurring late in an ACS window are obscured in the pooled average. Declarations from the first two years of each window, which have three to five years to appear in that window’s average, produce the same precise null as the overall same-window estimate ($\beta = -0.00032$; $p = .429$; approximately -0.006 standard deviations; MDE = 0.022 standard deviations). Declarations from the final three years are also null. In a joint model including early-window, late-window, and prior-window exposure, no coefficient reaches statistical significance, and the

prior-window coefficient remains marginally positive. The null early-window estimate provides no evidence that within-window timing masked an effect.

The drop-COMMC sensitivity analysis also yields the same overall conclusion for the during-window term, indicating that the null bonding pattern is not driven by the measurement break in the communication-capacity indicator. A positive prior-window association appears under both bonding-index constructions ($p = 0.24$) with the original 10-indicator measure; $p = .009$ after excluding COMMC). These estimates come from disclosure rows outside the preregistered sets of tests, so I treat them as exploratory. Their direction is consistent with the prior-window pattern described above.

These analyses leave the central pattern unchanged. The primary fixed-effects estimate is close to zero and precisely estimated. The preregistered first-difference model and matched contrast are null. The cross-sectional exposure gap narrows after matching, and the subindex models reveal no meaningful hidden movement. The evidence supports the conclusion that recurrent FEMA-declared disaster exposure is not associated with meaningful change in composite county social capital across the five-year ACS periods observed in this study.

5. Discussion

This paper asked whether recurrent FEMA-declared disaster exposure reshapes county-level social capital in the United States. The data do not support that it does, at least not in the form captured by a multidimensional county-level Social Capital Index over five-year ACS periods. The lower social capital observed in more highly exposed counties is consistent with baseline county differences and is not indicative of within-county erosion. When counties are compared to themselves over time, or to baseline-similar peers within the same broad region,

FEMA-declared exposure is not associated with meaningful change in composite social capital or in bonding, bridging, or linking social capital.

These findings extend Kyne, Aldrich, and Kyei's (2026) validation of SoCI as a predictor of disaster outcomes. Their analysis shows that higher social capital is associated with lower damages and injuries, supporting the interpretation of SoCI as a meaningful community resilience resource. The present analysis examines the other side of that relationship, showing that recurrent FEMA-declared exposure does not measurably alter composite county social capital over the observed five-year ACS windows. The findings suggest that social capital is associated with disaster outcomes while remaining a relatively stable feature of place across repeated disaster exposure.

The paper makes the following contributions to disaster and social-capital research. First, it shifts the outcome from organizational counts to multidimensional county social capital. Prior U.S. studies show that disasters can affect social-capital organizations, although organizational growth or decline does not necessarily indicate broader movement in bonding, bridging, or linking social capital at the county level. Second, it shows that null effects can be informative when they are precise and compared with a meaningful-effect threshold set in advance. The primary design can detect effects far smaller than the threshold treated as meaningful, which rules out insufficient statistical power as the main explanation for the null. Third, it clarifies the meaning of cross-sectional differences between disaster-prone and less disaster-prone places. Those differences are descriptively real. They should not be interpreted as disaster effects without accounting for baseline sorting.

Theoretically, the findings suggest that county social capital behaves more like a stable background condition than a short-term response to disaster exposure. Disasters may trigger

short-term solidarity, volunteering, mutual aid, organizational mobilization, institutional outreach, and the emergence of new groups and networks (Drabek and McEntire 2003; Dynes 2006; Landau et al. 2021), as well as distrust, conflict, displacement, or unequal access to recovery resources. They may also strain organizations, disrupt networks, and intensify existing inequalities (Smiley, Howell, and Elliott 2018). The results do not deny these possibilities. They show that such consequences do not necessarily aggregate into measurable movement in the broader county social-capital structure captured by SoCI. At this spatial and temporal scale, the observed stability is more consistent with durable demographic, institutional, and organizational arrangements than with short-term disaster-driven change.

This distinction is central to this paper. The findings should not be read as evidence that disasters have no social consequences. They show that a national county-level index is better suited to detecting broad structural change than localized, uneven, or short-lived forms of social disruption. A county can show stable aggregate social capital while particular neighborhoods, organizations, or population groups experience substantial strain. Organizational density can also appear stable even as individual organizations lose staff capacity, exhaust reserves, narrow services, or absorb greater demand. Linking scores can remain unchanged while residents or community organizations experience recovery institutions as difficult to access, unevenly responsive, or politically constrained.

The implication is about scale. National county-level analyses are valuable because they can identify broad patterns, test average relationships, and distinguish cross-sectional sorting from within-county change. They also flatten local heterogeneity. They cannot fully capture how disasters are experienced within counties, how social ties are redistributed across groups, or how community organizations absorb disruption beneath a stable aggregate surface. The durability

documented here therefore reinforces the need for local-level examinations. If county social capital remains stable in aggregate, the next empirical question is where disaster pressure shows up when it does not appear in the national county index.

This scale-bounded interpretation also clarifies how the findings relate to prior organizational-count studies. Wang and Ganapati (2018), Smiley, Howell, and Elliott (2018), and Michael et al. (2022) show that disasters can affect organizational infrastructure. The present analysis shows that those organizational changes do not necessarily scale up into movement in a broader multidimensional county index. In short, disaster exposure can reshape parts of the local civic and nonprofit infrastructure without changing the composite social-capital structure of the county as a whole.

5.1. Limitations

The findings should be interpreted within several measurement and design limits. First, FEMA declarations are administrative records of federally recognized disaster exposure. They do not directly measure physical hazard intensity, damage, mortality, displacement, or perceived disruption. They are appropriate for identifying counties that entered the federal disaster-declaration system. However, they exclude undeclared events, localized impacts below the declaration threshold, or variation in severity among counties covered by the same declaration.

Second, the panel is built from five-year ACS periods. ACS five-year estimates are pooled period estimates, which makes them appropriate for comparing county-period conditions across non-overlapping windows. This structure limits the analysis's temporal sensitivity. Short-lived changes in social capital that emerge immediately after a disaster and dissipate before they appear in a five-year average may not register in this study's research design. The timing checks

reported in Section 4.5 indicate that declarations arriving late in a window do not explain the null result. Genuinely transient effects remain beyond the reach of pooled period estimates. The panel also contains only three waves. County fixed effects and first differences control for stable county differences. With only three observations per county, the data do not support fine-grained dynamic treatment analyses or detailed tests of short-term recovery trajectories.

Third, SoCI is a county-level index built from publicly observable indicators of bonding, bridging, and linking social capital. It captures broad community structures, but it does not directly measure the internal health of specific organizations, the quality of social ties, informal mutual aid, residents' lived experience of institutional access, or the distribution of social capital across groups within counties. In particular, the bonding indicators cannot provide visibility into within-county segregation or unequal access to nominally present resources. A stable county-level index can therefore coexist with meaningful disruption for particular neighborhoods, organizations, or populations.

Finally, the paper estimates average effects across a national county panel. The results do not rule out heterogeneous effects in particular communities, hazard types, or dimensions of social capital that are too localized, too brief, or too unevenly distributed to move the national county-level estimate. The appropriate conclusion is therefore scale-bounded. Recurrent FEMA-declared disaster exposure is not associated with meaningful average change in county-level SoCI over the medium-run periods observed in this paper. The findings show that disaster-related social consequences are not visible as broad, systematic change in the national county-level index at this scale and over these time periods.

5.2. Future Research

Future research should pair county-level social-capital measures with finer-grained organizational and network data. If county social capital is stable in aggregate, the next empirical question is where the effects of disaster exposure appear over time when the aggregate index does not move. They may appear in organizational reserves, staffing, burnout, leadership burden, mission narrowing, informal mutual aid, or unequal access to linking institutions. Administrative organizational counts, county indexes, surveys, interviews, and local network data each capture a different part of that process. The stability of social capital documented here makes those lower-level processes important.

Future work should also test whether alternative exposure measures produce the same pattern of durability. Federal Emergency Management Agency (FEMA) declarations capture federally recognized disaster governance, but other data sources may capture different aspects of hazard exposure and impact. Damage estimates from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), hazard-event records from the National Oceanic and Atmospheric Administration (NOAA), insurance claims, disaster-assistance flows, or remotely sensed hazard measures may each reveal dimensions of exposure that declaration data cannot capture. Finally, the paper's equivalence-oriented approach could be extended to other county-level resilience indicators. Precise null results are often treated as failed findings, but in resilience research they can help identify which social structures are stable enough to function as background conditions instead of short-run outcomes.

6. Conclusion

Social capital is often described as a resource communities draw on when disasters occur. This paper asked whether recurrent FEMA-declared disaster exposure changes that resource at the county level. Across a national three-wave panel, the analysis finds no meaningful average

change. Composite social capital shows no meaningful within-county movement as FEMA-declared exposure rises or falls. The cross-sectional disadvantage of disaster-prone counties is more consistent with stable baseline differences than with detectable disaster-driven erosion. Bonding, bridging, and linking subindices likewise reveal no hidden disaster effect.

County-level social capital, measured through a multidimensional public-data index, appears durable across recurrent FEMA-declared disaster exposure. Disasters can activate, strain, and redistribute social relationships without producing corresponding change in the county's broader social-capital structure. This stability is itself an important finding for disaster sociology and resilience research. It clarifies the scale at which county social-capital indexes are informative and identifies the forms of change they are unlikely to capture. Understanding how communities and organizations absorb repeated disruption therefore requires more granular evidence capable of revealing strain beneath stable aggregate patterns.

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Appendix: Supplemental Tables

Table 1. SoCI Indicator Crosswalk

Subindex	Indicator code	Description	Source
BONDG	RACSI	Racial composition / fractionalization	ACS
BONDG	ETHSI	Ethnic/Hispanic composition / fractionalization	ACS
BONDG	EDUEQ	Educational equality	ACS
BONDG	INCEQ	Income equality (1 - Gini)	ACS
BONDG	EMPEQ	Employment equality	ACS
BONDG	RINCEQ	Racial income homogeneity	ACS
BONDG	GISEQ	Gender income similarity	ACS
BONDG	LANGC	Language competency	ACS
BONDG	COMMC	Communication capacity	ACS
BONDG	NONEL	Non-elder population share	ACS
BRIDG	RELDN	Religious organizations per 1,000 population	NaNDA
BRIDG	CIVDN	Civic organizations per 1,000 population	NaNDA
BRIDG	VETDN	Veterans organizations per 1,000 population	NaNDA
BRIDG	YUTDN	Youth organizations per 1,000 population	NaNDA
BRIDG	RELADN	Religious organizations per square mile	NaNDA
BRIDG	CIVADN	Civic organizations per square mile	NaNDA
BRIDG	VETADN	Veterans organizations per square mile	NaNDA
BRIDG	YUTADN	Youth organizations per square mile	NaNDA
LINKG	PLINK	Political linkage	ACS
LINKG	LOGLK	Local government workers per 1,000 population	ACS
LINKG	STGLK	State government workers per 1,000 population	ACS
LINKG	FEDLK	Federal government workers per 1,000 population	ACS
LINKG	RELPI	Religious-organization employees per 1,000 population	NaNDA
LINKG	CIVPI	Civic-organization employees per 1,000 population	NaNDA
LINKG	VETPI	Veterans-organization employees per 1,000 population	NaNDA
LINKG	YUTPI	Youth-organization employees per 1,000 population	NaNDA

Note. COMMC was retained in the primary BONDG construction to maintain its alignment with the updated SoCI indicator set, but it was omitted in the sensitivity specification because the underlying ACS B25043 communication-access item changes between 2018 and 2019, shifting from telephone service availability to computer/internet access and weakening over-time comparability.

Table 2. County Panel Construction and Exclusions

Stage	Unique geographies	Rows	Action
After one-to-one FIPS harmonization	3,136	9,403	Shannon County, SD renamed as Oglala Lakota County, SD; Wade Hampton Census Area, AK renamed as Kusilvak Census Area, AK
Final balanced panel	3,133	9,399	Complete county, SoCI, FEMA, and centroid information for every wave

Note. The source universe covers the 50 states and the District of Columbia before exclusions; Connecticut and the U.S. territories were excluded upstream because of Connecticut’s 2022 county-equivalent reorganization (see Section 3.1). The reduction from 3,136 to 3,133 geographies drops county-equivalents lacking complete SoCI, FEMA, and centroid information in every wave.

Table 3. Full Preregistered Results

Analysis and term (ID)	Measure	Estimate	SE	p	q	MDE (SD)
Same-window fixed effects (C1)	Composite SoCI	−0.00039	0.00032	.213	.342	0.024
Same-window term, during-plus-prior model (C2)	Composite SoCI	−0.00021	0.00032	.498	.498	0.024
Prior-window term, during-plus-prior model (C2)	Composite SoCI	0.00059	0.00030	.052	NA	NA
First difference (C8)	Composite SoCI	−0.00043	0.00027	.120	.342	0.047
Matched difference-in-differences (C3)	Composite SoCI	−0.00152	0.00134	.257	.342	0.178
Matched DiD, bridging subindex (C3-BRIDG)	Bridging (BRIDG)	0.00038	0.00058	.508	NA	NA
Fixed effects on matched sample (C3-TWFE)	Composite SoCI	0.00011	0.00048	.826	NA	NA
Same-window fixed effects, bonding (C4-BONDG)	Bonding (BONDG)	−0.00091	0.00080	.256	.384	0.021
Same-window fixed effects, bridging (C4-BRIDG)	Bridging (BRIDG)	−0.00039	0.00018	.027	.082	0.021
Same-window fixed effects, linking (C4-LINKG)	Linking (LINKG)	−0.00002	0.00031	.951	.951	0.026

Note. Rows correspond to the frozen county preregistration run; q-values are shown only within the preregistered families. NA marks terms outside the corrected families. The augmented first-difference and recent three-year checks appear in Table 4.

Table 4. Robustness and Exploratory Disclosures

Specification	Estimate	SE	p
Timing and Exposure Checks			
First difference with newly exposed indicator	−0.0008 4	0.00036	.019
Linking, recent three-year exposure	−0.0000 3	0.00035	.930
Composite SoCI, early-window exposure only	−0.0003 2	0.00041	.429
Composite SoCI, early term (early and late jointly)	−0.0003 1	0.00041	.446
Composite SoCI, late term (early and late jointly)	−0.0004 5	0.00035	.204
Composite SoCI, prior-window term (early, late, and prior jointly)	0.00056	0.00030	.066
COMMC Sensitivity Checks			
Bonding, ten-indicator measure, same-window exposure	−0.0004 2	0.00081	.605
Bonding, ten-indicator measure, prior five-year exposure	0.00160	0.00071	.024
Bonding without COMMC, same-window exposure	−0.0007 7	0.00094	.414
Bonding without COMMC, prior five-year exposure	0.00207	0.00079	.009

Note. These checks are disclosed but do not alter the primary result. The timing split was added post-freeze to assess whether late-window declarations had too little time to register in ACS pooled estimates. The COMMC sensitivity rows compare the primary ten-indicator bonding measure with a nine-indicator version that excludes COMMC. The early-window-only row is the estimate quoted in Section 4.5. The prior five-year composite estimate appears as the prior-window term in Table 3.

Paper 2: Threat-Informed Investment: A Diagnostic Framework for Resilience in Community-Based Organizations

Abstract

Community-based organizations (CBOs) deliver essential services during acute shocks and chronic disruption while operating with limited financial and administrative capacity. Organizational-resilience frameworks, however, often treat the external environment as generalized adversity. This approach obscures how distinct threats shape the capacities organizations build, draw down, or improvise. Nonprofit studies remain largely organized around single events and rarely explain how different threat types generate different resource investment patterns (Linnenluecke 2017; Raetze et al. 2022; Hepfer and Lawrence 2022). Drawing on coded threat-response episodes from interviews with leaders of 50 U.S. CBOs across 28 states, this paper develops the Organizational Resilience Threat-Informed Investment Framework (OR-TIIF). The framework treats the threat environment as a differentiated empirical input and produces a descriptive capacity-investment profile, not a resilience score. Findings show that most investments are threat-coupled. Financial, technological, and staffing threats tend to prompt investments in the corresponding capacity domain. Health and demand shocks prompt operational process changes, while planning concentrates around forecastable hazards. Social capacity is the central exception. It operates across every threat type as a standing connective infrastructure, independent of immediate threat response. Political and regulatory threats mark the boundary of capacity-investment logic. They often elicit advocacy, organizing, coalition building, and public positioning tactics because internal investment cannot resolve a hostile policy change or regulatory constraint. To clarify, funding disruptions caused by political

decisions, including grant freezes and cuts, are classified as financial threats because they call forth internal financial investment. The OR-TIIF identifies what organizations have on hand, what they draw down, what they rebuild, and whether their investments are standing capacities or reactive improvisations. This profile shows where resilience work is concentrated, where capacities are being depleted, and where investment gaps remain.

Keywords: organizational resilience; nonprofit resilience; community-based organizations; adaptive capacity; cumulative threat environments; organizational capacity investment; relational capacity; political and regulatory threats

1. Introduction

Guidance on organizational resilience typically prescribes what organizations should do, such as diversify funding, cross-train staff, or develop continuity plans. Underlying these recommendations is an assumption that organizational resilience is primarily a function of internal decisions. This study tests a different proposition, that the capacities organizations build, draw down, rebuild, or improvise are shaped by their threat environment, understood in this study as the particular mix of threats they face. Community-based organizations (CBOs) provide an ideal setting to examine this relationship. They are locally embedded, often resource-constrained, and perform critical community functions (Chillag et al. 2002; De Vita et al. 2008; Hutton et al. 2021), making them both vulnerable to and shaped by the threat environments in which they operate. Their work also relies on external funding, regulatory stability, partner networks, volunteer labor, and community trust. Those dependencies can themselves become sources of disruption.

CBOs deliver services, mobilize volunteers, connect residents to resources, translate local needs to public institutions, and often remain present long after formal emergency systems have moved on (Graham, Debucquoy, and Anguelovski 2016; Landau et al. 2021; Bezboruah et al. 2024; De Oro 2025). Disaster and community-resilience scholarship therefore frequently treats them as part of the social and organizational infrastructure that enables community resilience. Yet this literature more often examines what CBOs contribute to community resilience than how they sustain the organizational capacity that makes those contributions possible. If CBOs are expected to anchor community resilience, organizational-resilience scholarship must explain how they build, activate, replenish, and sustain their own capacity under chronic, layered, and increasingly politicized disruption.

When CBO leaders described the threats their organizations had faced, they rarely described a single hazard with a clear beginning and end. Instead, they described cumulative threat environments in which financial pressure, political and regulatory uncertainty, staffing strain, demand shifts, health disruption, technical failure, violence and safety concerns, and natural hazards overlapped, often before prior disruptions had resolved. This framing changes what a CBO resilience framework must explain. Existing frameworks do recognize environmental turbulence. The limitation is that the external environment enters these frameworks as generalized uncertainty or adversity. That framing flattens a configuration of distinct but interconnected threats. This flattening obscures how threat type shapes which capacities organizations build, draw down, replenish, or improvise and where internal capacity investment can reach its limits.

This limitation is especially consequential for CBOs, whose resilience challenges differ from the dominant firm-centered case studies in business and management research. Much of

that literature frames resilience around continuity, performance recovery, and competitiveness. CBOs, by contrast, must continue mission-driven work under restricted funding, community accountability, thin administrative margins, relational obligations, and dependence on funders and regulators whose decisions can themselves become sources of disruption. Emerging nonprofit-resilience frameworks better reflect the constraints under which CBOs operate, but they still tend to emphasize survival during a financial crisis, tactics used during a named disruption, or broad proactive attributes such as awareness, adaptability, shared values, and slack (Kedia et al. 2025). What they do not explain is how varied threat types call forth different patterns of capacity investment or where capacity-building becomes insufficient as a response.

This paper asks: How do the threats that make up CBOs' operating environments shape the resilience capacities they build, activate, or draw down? This paper analyzes semi-structured interviews with leaders of 50 CBOs across 28 states and all four U.S. Census regions (West, Midwest, South, Northeast). Recruitment used a multi-stage design intended to capture variation in county disaster-exposure cadence, defined by the frequency and recency of FEMA major-disaster declarations, as well as geographic region, organizational size, and service type. Although recruitment was partly structured around hazard exposure, the interviews elicited the broader threat environments leaders actually faced. Using an abductive approach, I identified 326 threat-response episodes across the interviews, each defined as one organization's encounter with one threat and its corresponding response. I then coded each capacity investment by domain, mode, and approach and compared investment patterns across threat types. *Domain* captures what capacity the organization invested in: Financial, Technological, Social, Human Capital, Operational, or Planning. *Mode* distinguishes resource stocks from process practices, while

approach distinguishes standing capacities from reactive investments mounted in response to a threat.

The analysis yielded the Organizational Resilience Threat-Informed Investment Framework (OR-TIIF), a grounded analytic framework that can also be used as a diagnostic tool. The OR-TIIF treats the threat environment as the input and an organization's capacity-investment profile as the output. As an analytic framework, it distinguishes which capacities organizations invest in, how those capacities function, and whether they were already in place or mounted in response to a threat. As a diagnostic tool, it helps organizations and funders examine the investments an organization has made in relation to the threats it faces. It is intentionally not a scored instrument because no single investment profile is appropriate across all threat environments. Threats rarely occur independently and often intersect and compound one another. An organization's investment posture should therefore be interpreted in relation to the particular configuration of pressures it faces. Recurring flood exposure, for example, may be layered with chronic political pressure, persistent staffing strain, and repeated demand surges.

This paper makes five key contributions to the literature. First, the threat environment is an analytic input in its own right. Which threats an organization faces, and in what combination, shapes which capacities it builds, activates, or draws down. Second, firm-centered resilience assumptions require reworking for CBOs. The relevant outcome is not simply performance recovery or operational continuity, but mission-sustaining capacity under funder, regulator, staffing, and community-accountability constraints. Third, capacity investments are threat-coupled, but unevenly so. Threats that deplete a recognizable stock often prompt investment in that same stock; threats without a corresponding stock are more often absorbed through process change. Fourth, relational capacity is a central and distinctive domain. Social investments appear

across every threat type, are the most common investments overall, and usually operate as standing infrastructure. Fifth, preparedness is not limited to formal planning; it is built through financial, social, operational, technological, human-capital, and planning investments that are already in place before threats fully materialize. The findings also identify a boundary condition for capacity-investment logic: political and regulatory threats often cannot be solved by building internal capacity alone. When grants freeze or regulatory constraints narrow action, organizations respond through organizing and coalition building.

The remainder of the paper proceeds as follows. Section 2 situates the framework in the organizational-resilience, nonprofit-resilience, and practitioner-tool literatures. Section 3 describes the sample, the episode-based coding strategy, and the development of the OR-TIIF. Section 4 presents the empirical patterns that shaped the framework. Section 5 discusses its theoretical contribution, practical use, limitations, and future directions. Section 6 concludes by returning to the study's central claim that CBO resilience is best understood not as a universal capacity score, but as a threat-informed investment profile that shows what organizations have on hand, what they draw down, what they rebuild, and where capacity investment reaches its limits.

2. Background

2.1. External Context Recognized, but Undertheorized

Organizational resilience has become a large and fragmented literature. Reviews in business and management find different streams treating resilience as response to external threats, reliability, employee strength, business-model adaptability, or supply-chain vulnerability reduction (Linnenluecke 2017; Raetze et al. 2022; Su and Junge 2023). Capability-based

accounts define organizational resilience as a set of capacities through which organizations anticipate potential threats, cope with adverse events, and adapt afterward (Duchek 2020). Research on crisis management distinguishes between crises as discrete events and crises as ongoing processes. Newer work on dynamic capabilities, entrepreneurship, supply chains, and organizational time treats resilience as continuous adaptation under volatile conditions, not as a return to a pre-crisis state (Williams et al. 2017; Manfield and Newey 2018; Wieland and Durach 2021; Shepherd and Williams 2023). This scholarship recognizes that organizations operate in unstable environments. Context itself, though, remains undertheorized, standing in as a general condition of adversity or disruption. What that framing leaves out is the differentiated threat environment that structures organizational response capacity.

Some adjacent literatures move closer toward the argument I develop in this paper. Manfield and Newey (2018), for example, argue that familiar threats call for different capability responses than complex and infrequent threats. Supply-chain resilience research often distinguishes supply disruptions, demand surges, logistics failures, and other disruption types. Shepherd and Williams (2023) show that organizations encountering the same COVID-19 shock followed different response paths depending on whether the shock produced demand shifts or operational threats. Together, these studies help establish that threat characteristics are important factors in shaping what kind of response or capability an organization needs. What they do not provide is a CBO-specific framework that links multiple external threat types to the capacities organizations build, deplete, replenish, or reconfigure over time.

Dominant business and management frameworks are built from studies of private-sector firms, high-reliability systems, supply chains, and crisis-management contexts, where continuity, competitiveness, and performance are the central outcomes. These frameworks are valuable for

theorizing capability, adaptation, and continuity, but they miss four features especially relevant to CBOs. First, CBOs are mission-bound. They are expected to remain responsive to community need even when doing so worsens their internal strain. Second, CBOs are structurally dependent on funders, contracts, regulators, volunteers, and community trust, which makes the external environment part of their operating infrastructure as well as a source of shocks. Dependence on external actors is not necessarily unique to CBOs; firms answer to investors, customers, and regulators, and public agencies to lawmakers and budgets (Pfeffer and Salancik 1978). What distinguishes CBOs is the configuration of that dependence. The resources they rely on are rarely secured by market revenue, and volunteer labor and community trust cannot be quickly rebuilt once depleted. Third, relational capacity operates as the standing condition that makes response to many different threat environments possible. Fourth, CBOs absorb cumulative drawdowns. Repeated threats deplete the resources and processes organizations rely on over time, and a CBO resilience framework must account for that accumulation.

The OR-TIIF introduced in this paper sharpens growing scholarly attention to organizations' external operating environments. Existing frameworks recognize that organizations operate amid volatility, uncertainty, and disruption. The unresolved problem is how to operationalize that environment as a differentiated threat structure and link it to observed investment behavior.

2.2. Gaps in Nonprofit Resilience Frameworks

Nonprofit-specific organizational-resilience research is more attentive to the conditions under which the smaller CBOs examined in this paper operate. Nonprofits are mission-bound organizations that must remain accountable to their communities while also operating under

resource dependence, restricted funding, and volunteer and staff constraints (Mosley, Maronick, and Katz 2012; Young 2022). De Oro (2025:38) argues that nonprofits contribute to the adaptive capacity of the communities in which they are embedded and cannot fulfill their missions apart from the people and systems that sustain them. These relationships can supply critical capacity during disruption, but they can also transmit financial, political, and regulatory pressure into the organization. For this reason, nonprofit resilience cannot be reduced to business continuity or performance recovery. It should also account for mission, legitimacy, relational embeddedness, and the tactics organizations use to keep operating under constraint (Searing, Wiley, and Young 2021; Bomsta and Kerr 2023). I focus on three strands of this literature. Each advances the study of nonprofit resilience, but none fully explains how different threat types shape the capacities CBOs build, activate, deplete, or improvise under pressure.

One strand examines financial vulnerability, fiscal shocks, and organizational survival. Searing, Wiley, and Young's (2021) Nonprofit Resiliency Framework, based on nonprofits navigating the Illinois budget impasse, shifts attention from predicting closure to identifying the tactics through which organizations continue service delivery during financial crisis. Funding cuts, grant freezes, and reimbursement delays can immediately threaten payroll and service continuity. But fiscal survival captures only one part of organizational resilience. What does chronic and cumulative disruption do to the less visible capacities that allow a CBO to function over time, such as retaining staff and maintaining the relational ties that drive mission work? An organization can keep its doors open and still be depleted along these dimensions, and some short-term survival tactics preserve services by drawing down the human and relational infrastructure that makes future adaptation possible.

A second strand examines nonprofit resilience during named disruptions, especially natural hazards (Chen 2022) and public-health emergencies (Maher et al. 2020; Hutton et al. 2021). These studies show how organizations adapt under real pressure instead of in abstract planning scenarios, and they bring nonprofit values, client relationships, and community into view. Bomsta and Kerr's (2023) study of intimate-partner-abuse nonprofits during COVID-19 adapts a for-profit resilience model to a nonprofit setting by adding mission and environmental context to technical, social, and financial resources. This expansion recognizes that nonprofit resilience depends on more than internal management capacity or financial position. But because each study is anchored in one named event, this strand shows how organizations respond to a particular disruption without showing how response varies across the several threats an organization might face at once.

A third strand attends to relationships, which nonprofit frameworks acknowledge more readily than business-oriented models do (Bomsta and Kerr 2023). For CBOs, relationships are not simply external supports that can be mobilized after disruption. They are part of how ordinary work gets done, from reaching clients to coordinating services and maintaining community legitimacy (De Oro 2025). But even where frameworks name social resources, they stop at naming them explicitly. Relationships appear as one resource domain among others, not as a set of distinct mechanisms. Additionally, existing work rarely asks whether relational capacity is built before disruption or improvised during it, whether it is depleted by repeated use, or how it differs from internal staffing capacity.

Recent work on proactive nonprofit resilience addresses a related limitation by shifting attention from recovery after adversity to capacities built before disruption. Kedia et al. (2025) argue that nonprofit-resilience research has adopted a largely reactive lens, and propose a

proactive framework organized around awareness, adaptability, shared values, and slack across individual, organizational, and network levels. This broadens the discussion, but it does not explain how different threats lead organizations to invest in different capacities, which capacities are drawn down under particular conditions, or when internal capacity-building cannot address political or regulatory pressure.

Disaster research has also examined CBOs and local nonprofits directly. Longitudinal work following Hurricane Katrina traces local nonprofits being drawn into formal disaster-management roles across a decade of recovery while continuing to carry chronic community burdens (Jenkins et al. 2015). Studies of homeless-serving organizations document a related pattern. For organizations whose clients live in constant crisis, every day is a disaster, and formal disaster planning competes with these chronic service demands (Vickery 2015; Balut, Gin, and Dobalian 2025). These studies touch on two themes examined in this paper. CBOs operate under chronic pressure, and the demands that come along with formal preparedness can exceed their operational capacity.

Taken together, nonprofit resilience scholarship has expanded the organizational-resilience conversation by foregrounding financial vulnerability, mission, tactics, and social resources. But it tends (1) to remain anchored in a single crisis², sector³, or place⁴; (2) to treat the

² Including a proliferation of research on how nonprofits maintained operations during the COVID-19 pandemic (Maher, Hoang, and Hindery 2020; Dayson et al. 2021; Hutton et al. 2021; Newby and Branyon 2021; Cohen et al. 2022; Coll et al. 2023; Herrero and Kraemer 2022; Karadzhev et al. 2022; Bomsta and Kerr 2023; Miao, Schwarz, and Ahmad 2026).

³ Comparative studies across multiple CBOs remain rare, and those that do exist often focus narrowly on specific subsectors such as human services (Kimberlin, Schwartz, and Austin 2011), syringe exchange programs (Lune 2002), mental health (Searing 2020).

⁴ Concentrated in specific metropolitan areas like New York (Searing 2020; Lune 2002) and San Francisco (Cohen et al. 2022; Kimberlin, Schwartz, and Austin 2011).

external environment as general context instead of a differentiated set of threat types; (3) to acknowledge relationships without theorizing relational capacity as a durable and potentially depleted infrastructure (Witmer and Mellinger 2016; Kuntz, Malinen, and Näswall 2017; De Oro 2025); and (4) to leave unmarked the boundary between capacity investments an organization can build internally and tactics it must use when a threat cannot be solved through internal capacity. These gaps are especially consequential for CBOs facing increasingly chronic, cumulative, and politicized threat environments.

2.3. Threat Environments and Resource Dependence

The concept of a *threat environment* links organizational-resilience theory to nonprofit resource dependence. By threat environment, I mean the set of external pressures, actors, and conditions that can disrupt a CBO's mission work, deplete the capacities it relies on, constrain the responses available to it, and accumulate or interact over time. In this study, a CBO's threat environment is composed of one or more of eight threat types (financial, hazard/environmental, staffing/personnel, demand/client, political/regulatory, health/pandemic, technical/infrastructure, and violence/safety). It may center on a single type or on several that overlap and compound. CBOs depend on external actors for money, regulatory permission, referrals, volunteers, and community trust (Pfeffer and Salancik 1978). That dependence builds external disruption into the organization's operating model instead of leaving it as an occasional background condition. A grant freeze can threaten payroll. A policy change can narrow eligibility rules or chill outreach. A local hazard can disrupt both clients and staff. A public-health emergency can make the organization's core service model impossible. These threats differ not only in severity and timing but in which capacities they deplete and which responses they make possible.

For CBOs, resilience therefore looks less like preparing for a single scenario and more like managing a portfolio of resource stocks and processes under repeated drawdown. Some capacities can be held on hand, such as reserves, technology, partner ties, and institutional knowledge. Others are held as practices, such as prioritizing which needs to meet first, service-model pivots, cross-training, and continuity planning. The practical question is not only, “What event might happen?” but, “What do we have available, what do we expect to draw down when certain threats accumulate, what do we replenish afterward, and what might we be forced to invent in the moment?”

Resource-based accounts of disaster and organizations provide a starting point. Gregg and colleagues (2022), building on conservation-of-resources theory, argue that disaster exposure depletes or prompts investment in individual, team, and organizational resources, with consequences for organizational outcomes (Gregg et al. 2022). That depletion/investment logic travels well to some CBO threats. Financial threats deplete money, technical failures deplete technological infrastructure, staffing crises deplete continuity and labor capacity, and in those cases, the response often looks like in-kind replenishment. But, as the findings in this study demonstrate, not all threats deplete a matching stock. A pandemic disrupts how work is done; a demand surge overwhelms throughput; a policy shock changes the rules under which the organization operates. These threats often require process reconfiguration not stock replacement. Political and regulatory threats are the clearest limiting case. If a grant is retracted, a contract is suddenly uncertain, a state rule changes eligibility, or a federal policy threatens the organization's client base, the organization may not be able to “invest” its way out of the problem. It may need to advocate, reposition, form coalitions, or defend mission commitments. A CBO resilience

framework therefore needs a boundary between capacity investments an organization can build internally and tactics it must use when the threat sits outside its internal capacity portfolio.

2.4. The Limits of General Capacity Assessments

The practitioner landscape contains many nonprofit assessment tools, but most are not threat-informed. Informing Change's (2017) Hewlett Foundation–commissioned review catalogued 91 organizational capacity assessment tools, 48 of them multi-area assessments and 43 checklists and guides. The dominant genre is the scored self-assessment of general management capacity across leadership, governance, finance, and operations. These tools benchmark an organization's standing effectiveness. They do not ask how a particular threat environment sorts the investments an organization has made. The review's own headline finding is that the tool matters far less than the process it structures. The tools regarded most useful were adapted to the specific organization and facilitated as a conversation instead of administered as a score (Informing Change 2017).

Nonprofit-facing tools that engage threat directly, such as continuity-of-operations templates, emergency-planning trainings, and disaster-preparedness lists, are event-centered. They ask whether an organization can continue operating through a specified disruption. That is necessary work. A weather plan can clarify when to close a site, and a continuity plan can preserve access to data. But it is incomplete for organizations facing chronic, layered threats. A CBO may need a hurricane plan, but it also needs to know whether it has reserves, staff slack, and funder flexibility when the hurricane lands on top of a staffing crisis and a funding freeze. General capacity tools miss which threats deplete which capacities. Continuity tools miss what accumulates when threats arrive together. The OR-TIIF is built to fill this gap, not as a capacity

checklist or a single-event continuity plan, but as a reflective map that links an organization's threat environment to the capacities and practices it builds, activates, depletes, and rebuilds.

2.5. How the OR-TIIF Differs from Scenario Planning

Because the OR-TIIF is threat-informed and planning-relevant, it may be read as a variant of scenario planning. The distinction is important. Scenario planning usually starts with imagined future situations and works forward from them. The tradition associated with Wack's (1985) work at Royal Dutch/Shell and systematized by Schoemaker (1995) asks planners to construct a small set of plausible alternative futures and test strategic assumptions against them, asking what each future would require if it materialized. Nonprofit adaptations retain that prospective logic, narrowing it to a specific event or domain, such as whether revenue can absorb a projected shortfall or whether operations can continue through a specified disruption (The Bridgespan Group 2022; Candid n.d.; Propel Nonprofits n.d.). Scenario planning is therefore prospective and scenario-specific. It helps organizations prepare for plausible futures by clarifying assumptions, vulnerabilities, and contingent actions.

The OR-TIIF is not a substitute for scenario planning. The two approaches answer different questions and can be used in sequence. Scenario planning begins with a plausible future event and asks how the organization would respond. The OR-TIIF begins with the organization's current investment posture and asks how its resource stocks and operating processes align with the broader configuration of threats it already faces and can reasonably anticipate. It also reveals whether that posture was deliberately built or accumulated through repeated improvisation. An OR-TIIF assessment might show, for example, that an organization persistently absorbs funding shocks through staff overextension or assembles partnerships only after a crisis begins. A

subsequent scenario exercise could then test a more deliberate response to a specific future funding freeze or demand surge. For CBOs facing chronic and compounding threats, the question, “What would we do if X happened?” comes second. Organizations should first ask, “What have we been relying on across the threats we face, where are we still improvising, and is this the posture we intend to sustain?”

3. Methods

3.1. Study Design and Sample

This paper draws on 50 in-depth interviews with leaders of community-based nonprofit organizations across the U.S. (Figure 1). The first recruitment phase used a multi-stage stratified design built from two public data sources: FEMA (2026) major-disaster declarations (excluding COVID-19), and American Community Survey five-year estimates for 2019–2023 (U.S. Census Bureau 2024). Counties were classified by disaster-exposure cadence, defined as declaration frequency crossed with declaration recency. A second recruitment phase broadened the sample toward more even coverage across four CDC/NCHS (2024) regions (West, Midwest, South, Northeast), and deliberately recruited more environmental-justice organizations, a theoretically motivated choice after early interviews suggested that these organizations often face chronic, structural disruption, not primarily episodic shocks. Eligible organizations were community-rooted nonprofits with at least three years of history and work in direct service, advocacy, organizing, or intermediary support. Contacts were identified through ProPublica’s Nonprofit Explorer, state association lists, county directories, and targeted web searches. Interviews were semi-structured, usually 45–60 minutes, conducted over Zoom or Microsoft Teams with consent,

and are reported here in aggregate, de-identified form under IRB approval (#25-10-44).

Sample Demographics

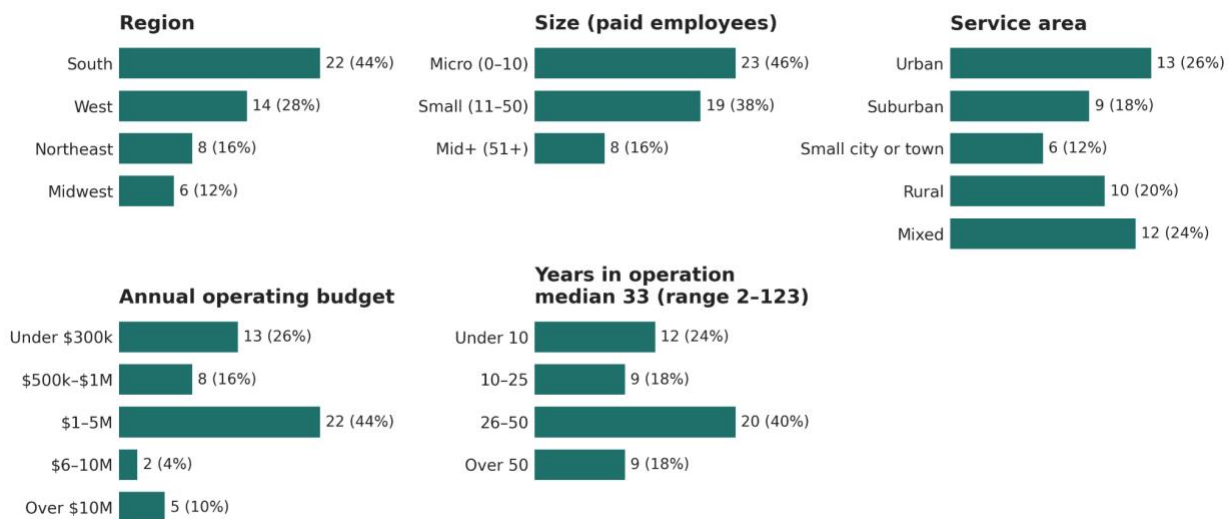


Figure 1. Sample Demographics

The sample included geographic and organizational variation relevant to developing a framework for use across diverse contexts. The organizations in the study represented 28 states and all four Census regions: South (22), West (14), Northeast (8), and Midwest (6). They also covered the full disaster-exposure grid used in the first recruitment phase, with most organizations located in a lower-frequency, lower-recency county (27 of 50). County exposure functions here as a sampling device instead of an explanatory variable, because hazard events did not dominate leaders' accounts even in the most disaster-exposed counties.

Hazard/environmental threats did not exceed 28 percent of coded episodes in any exposure stratum, so the analysis centers on the threat environments leaders themselves described (Section 4.1). Most of the organizations were small and locally rooted. Eighty-four percent employed fewer than 50 staff, and nearly all operated within a single county or state instead of as chapters of a national organization. Operating budgets ranged from under \$300,000 to over \$10 million,

with \$1–5 million as the most common category. Direct-service providers made up 62 percent of the sample (31 of 50), and advocacy or organizing organizations 32 percent (16 of 50). The organizations were well established, with a median of 33 years since receiving tax-exempt status, and roughly one-quarter were faith-based or faith-rooted. Interviewees were the most senior person in the organization in 80 percent of cases (40 of 50), most often an executive director, CEO, or founder. This profile aligns with the study's focus on organizational survival, since these leaders are the people most directly accountable for sustaining operations under disruption.

This geographic and sectoral variation allows the framework to capture patterns across diverse organizational contexts. Prior nonprofit-resilience studies that develop or adapt frameworks are typically anchored in a single setting, such as intimate-partner-abuse agencies during COVID-19 (Bomsta and Kerr 2023), nonprofits weathering a state budget impasse (Searing, Wiley, and Young 2021), or a single national nonprofit sector (Kedia et al. 2025). A framework drawn from one place and one crisis risks coding context-specific features as general structure. Grounding the OR-TIIF in 50 organizations across varied regions, hazard profiles, sizes, and service domains does not make the study a probability sample of the CBO sector. Participation skewed toward more-exposed regions, and because eligibility required organizations to be operational at the time of recruitment, the sample excludes CBOs that had already closed or ceased operations. The variation within the sample nonetheless allowed the framework's domains and indicators to be examined across multiple contexts instead of drawing them from only one. It also broadened the range of threats the framework had to explain. At the time of the interviews, organizations were not only reflecting on past experiences. Many were actively navigating a nationwide period of political and funding disruption that was reshaping their work, while also managing regulatory uncertainty, staffing strain, and rising demands for

their services. The OR-TIIF therefore had to account both for place-specific hazards and for broader pressures unfolding across organizations and communities at the same time.

3.2. Unit of Analysis: Threat-Response Episodes

I defined an episode as one organization's encounter with one threat and the corresponding response, using leaders' accounts to distinguish where one episode ended and another began or overlapped. This unit of analysis was necessary because the research question concerns how organizations respond to diverse threat environments, not whether an organization as a whole is resilient. I then coded each episode for threat type, the capacity affected, and the response. I also coded each episode for the threat's driver, whether the organization had faced it before, and the direction of the impact on capacity (depleting, unchanged, strengthened). Threats were grouped into eight types: financial, hazard/environmental, staffing/personnel, demand/client, political/regulatory, health/pandemic, technical/infrastructure, and violence/safety. The violence/safety category emerged during review of residual cases and, at five episodes, is reported cautiously. The final grid contained 326 episodes across 50 organizations. Episodes were nested within organizations and were not independent statistical observations. Counts are descriptive, and their value is that they make the distribution of threats and investments visible while retaining traceability to the underlying interview evidence.

3.3. Coding Capacity Investments

For each episode, I coded active internal resilience investments. An investment was counted only when the organization built, replenished, activated, or reconfigured a capacity relevant to its own ability to continue mission work. The coding excluded passive descriptions of

organizational state, passive receipt of resources, aspirations that did not materialize, failed attempts, ordinary program delivery to clients, and the threat's own impact or loss.

Coding followed the Framework Method, a matrix-based approach to organizing and analyzing qualitative data (Gale et al. 2013). I began with a preliminary organizational-resilience index that I had developed before this analysis by synthesizing for-profit organizational-resilience frameworks (Lee et al. 2013; Gregg et al. 2022; Bomsta and Kerr 2023) alongside the available nonprofit-resilience literature (Bandura 2000; Eriksson et al. 2001; Rodríguez-Sánchez and Perea 2015; Figley and Figley 2017; Vera, Rodríguez-Sánchez, and Salanova 2017; Manomenidis, Panagopoulou and Montgomery 2019; Singh, Martins and Tefera 2022; Koamesah, Virlia and Musa 2022; Ortiz-Calvo et al. 2022). That index extended existing tools by giving greater attention to environmental context, diverse threat exposure, social relations, and community embeddedness. I applied this index as a directed coding frame (Hsieh and Shannon 2005), while allowing the interview data to reshape the inherited structure where it did not fit.

To ensure the completeness of the coding, I reviewed all 326 episodes separately for each capacity domain and captured every relevant investment, including those missed in earlier coding rounds. During these passes, I assigned descriptive indicator labels to investments instead of coding them to a fixed final list. After the full corpus had been coded, I compared those labels, merged codes that captured the same underlying form of investment, and consolidated them into 33 final indicators. I then verified every retained investment entry line by line against its supporting quotation, checking whether it met the definition of an investment, whether it duplicated another entry, which final indicator it fit, and whether it was anticipatory or reactive.

Reviewing the full corpus this way reduced the risk of recovering only the investments anticipated by the initial coding frame.

At the coding stage, the 33 indicators were mapped to seven domains: financial, technological, social, staffing capacity, staff well-being, operational, and planning. Each retained capacity investment was assigned to one indicator and tagged for mode and approach. *Mode* distinguishes resource investments, which build or draw on a stock, from process investments, which change how the organization operates. Stocks include reserves, technology, relationships, and staffing capacity; processes include service-model pivots, emergency routines, and succession procedures. *Approach* distinguishes anticipatory investments, which were already in place and activated during the episode, from reactive investments, which were mounted because of the threat. This distinction provides the empirical basis for the framework's approach axis.

The final OR-TIIF collapses the seven coding domains into six. Staffing capacity and staff well-being are combined under Human Capital as two related but analytically distinct forms of investment in people. The original distinction remains in the coding methods, while the framework as presented uses the simpler structure. Investment coding overlaid episode coding, so a single episode could contain no retained investment, one investment, or multiple entries across domains.

3.4. Developing the OR-TIIF

The coding procedure described in the previous section produced a verified set of episode-level investment entries. I used those entries to develop the OR-TIIF abductively, moving repeatedly between a preliminary framework drawn from prior research and the patterns in the episode data (Timmermans and Tavory 2012). This process followed Lofland and

Lofland's (1995) view that the analysis develops through repeated efforts to organize and interpret the data. When recurring patterns did not fit the preliminary framework I had developed, I revised the structure.

I used three nonprofit-specific models as starting points. Searing, Wiley, and Young (2021) highlight the concrete tactics organizations use under fiscal constraint, although their framework is anchored in a single financial crisis and does not distinguish tactics from capacity investments. Bomsta and Kerr (2023) provided the closest domain-level precedent by incorporating technical, social, and financial resources, mission and values, and environmental context into a nonprofit-resilience model. Kedia et al. (2025) contributed the proactive lens, organizing resilience around awareness, adaptability, shared values, and slack across individual, organizational, and network levels.

Two additional bodies of work informed the framework's cross-cutting axes. Gregg et al.'s (2022) conservation-of-resources account focused attention on resource investment, depletion, and replenishment within threat-response episodes and informed the resource side of the mode axis. Duchek (2020), alongside Kedia et al.'s (2025) proactive framing, separates capacities developed before disruption from responses mounted as disruption unfolded. The episode data refined that distinction because capacities already in place were not necessarily built proactively for a specific threat. The final approach axis therefore distinguishes anticipatory (standing) capacity from reactive (threat-triggered) investment.

Four recurring mismatches between the preliminary framework and the episode data led to structural revisions. First, service-delivery pivots were one of the most common responses in the episode grid but had no clear home in a resource-centered structure. I therefore added *Operational* as a separate domain. Second, investments in the organization's own staff behaved

differently from investments in external relationships and partnerships, so I separated *Human Capital* from *Social*, consistent with scholarship treating human and social capital as distinct forms of capacity. In the coding structure, *Human Capital* was represented by the separate categories of staffing capacity and staff well-being; these were later brought together as two related but analytically distinct forms of investment in people. Third, the distinction between resource stocks and operating processes appeared across domains. I therefore treated resource versus process as a cross-cutting mode axis.

The fourth revision concerned the framework's overall hierarchy. An earlier version followed Lee, Vargo, and Seville's (2013) distinction between Adaptive Capacity and Planning, but that structure did not fit the episode data. Planning could be either anticipatory or reactive. About 64 percent of coded planning investments were mounted after a threat had already materialized. Because the distinction between advance preparation and reactive response also ran through *Planning* itself, it could not serve as the boundary separating Planning from Adaptive Capacity. The split was also lopsided. It grouped five domains under Adaptive Capacity and set Planning, a single domain, beside them as an equal category.

In the final OR-TIIF, Threat Environment frames the model, and Adaptive Capacity serves as the superordinate category encompassing six domains: Financial, Technological, Social, Human Capital, Operational, and Planning. In this paper, adaptive capacity refers to an organization's overall capacity to adjust to its threat environment, whether through resources already on hand, operating processes developed over time, formal plans, or responses improvised under pressure. This application is consistent with capability-based accounts that treat adaptation as part of a broader resilience meta-capability (Duchek 2020) and with disaster research showing that organizations adapt through both planned and improvised action (Kendra and Wachtendorf

2003). Using an existing plan is therefore treated as an expression of adaptive capacity, not as something outside it. The temporal distinction between capacities already in place and responses mounted after a threat is preserved in the approach axis, where it applies to investments in every domain.

The indicator structure was developed through the same iterative process. The working catalog described in Section 3.3 contained 41 provisional indicators. I reviewed it for recurrence, conceptual clarity, redundancy, and domain fit, then merged labels that represented the same underlying form of investment and reassigned their entries to the consolidated indicator within the appropriate domain. Merging labels did not remove valid investment entries. Entries were removed only when line-by-line review showed that they did not meet the definition of an active internal resilience investment. This process produced the final list of 33 indicators.

Because the OR-TIIF is an analytic typology and diagnostic map and not a psychometric scale, indicators were retained based on whether they represented recurring, clearly defined, and empirically supported forms of investment. The study was not designed to estimate indicator weights or validate a scored scale, and 50 organizations would not support that purpose. The aim was to produce a transparent framework that preserves meaningful distinctions in how CBOs build, activate, draw down, and reconfigure capacity under different threats. All domain, indicator, mode, and approach counts reported in the findings were calculated from a single verified episode-level master file.

During codebook and framework development, I used Claude (Anthropic 2026), accessed through the desktop application under Northeastern University's license, to surface candidate patterns and suggest possible codes from the de-identified transcripts. I treated these suggestions

as leads for evaluation, not as findings. All episode and investment coding was conducted by hand in ATLAS.ti, every retained code was verified line by line against its supporting quotation, and all coding and framework decisions were my own. This use followed Northeastern's AI Review Committee guidelines, which permit AI-assisted analysis of de-identified data through university-approved tools and prohibit entering identifiable participant data into AI systems.

3.5. Reliability and Scope

Because the coding and framework revision were conducted by a single researcher, I do not report an intercoder reliability statistic. The consistency of my coding rests on clearly defined inclusion and exclusion rules, repeated full-corpus reviews verifying each retained investment line by line against its supporting quotation, preserved coding files, and recalculation of all reported counts from one final episode-level dataset covering every episode.

This documentation process is not a substitute for independent reliability testing, but it is appropriate for the aim of the analysis, which was to develop a defensible grounded framework. The counts therefore describe patterns within this corpus and are not population estimates for the CBO sector. The analysis also makes no claim that any investment posture causes better organizational outcomes. That question belongs to future research and to the companion analysis of depletion and capacity change. As a descriptive check on the cross-tabulated patterns reported in Section 4.2, I also estimated separate binary logistic models on the episode-level dataset, each predicting whether an episode included an investment in a given capacity domain. The predictor was a binary indicator for the relevant threat type, and standard errors were clustered by organization to account for episodes nested within organizations. These models are reported only

to assess whether the diagonal patterns visible in Figure 4 persist after accounting for within-organization clustering. They include no covariates and are not causal estimates.

3.6. Framework Structure and Output

The finalized OR-TIIF structure is summarized in Table 1 and Figure 2. The threat environment is the input, mission and values are the interpretive lens, and adaptive-capacity investments are organized into six domains. Each investment is then tagged by its mode and approach. The framework's output is a descriptive investment profile. Thus for each organization the tool reveals the pattern of capacities invested in, by mode and approach, in response to its particular threat environment. Aggregated across organizations and cross-tabulated by threat type, these profiles constitute the threat-investment matrix that anchors the findings. Mission and values were not coded as an investment domain. They enter the framework as interpretive context because leaders repeatedly explained investment decisions in relation to mission commitments, organizational identity, and obligations to the communities they serve.

Table 1. OR-TIIF Domains, Analytic Roles, and Indicators

Domain	Function	Indicators
Financial	Financial flexibility and resource availability	reserves; diversification; fundraising/donors; cost reductions; grants/contracts
Technological	Technology, data systems, and infrastructure	adoption; infrastructure; governance
Social	Relationships used across threat types	partnerships/coalitions; support-seeking; volunteer engagement; internal relational capacity; funder relationships; community backing

Human Capital	Staffing capacity and staff well-being	staffing capacity: succession/continuity; hiring/retention; capacity reduction; role flexibility. staff well-being: recognition/morale; well-being program; time flexibility; crisis support
Operational	Service delivery and internal operations	program reconfiguration; service-model pivot; emergency mobilization; surge scaling; protective protocols; operational buffer; facility/space
Planning	Preparedness, continuity, safety, and strategic planning	disaster preparedness; continuity/risk planning; safety/security planning; strategic planning

Note. Human Capital consolidates the verified staffing-capacity and staff-well-being coding dimensions into one analytic domain while preserving their distinction in the indicator set.

Organizational Resilience Threat-Informed Investment Framework (OR-TIIF)

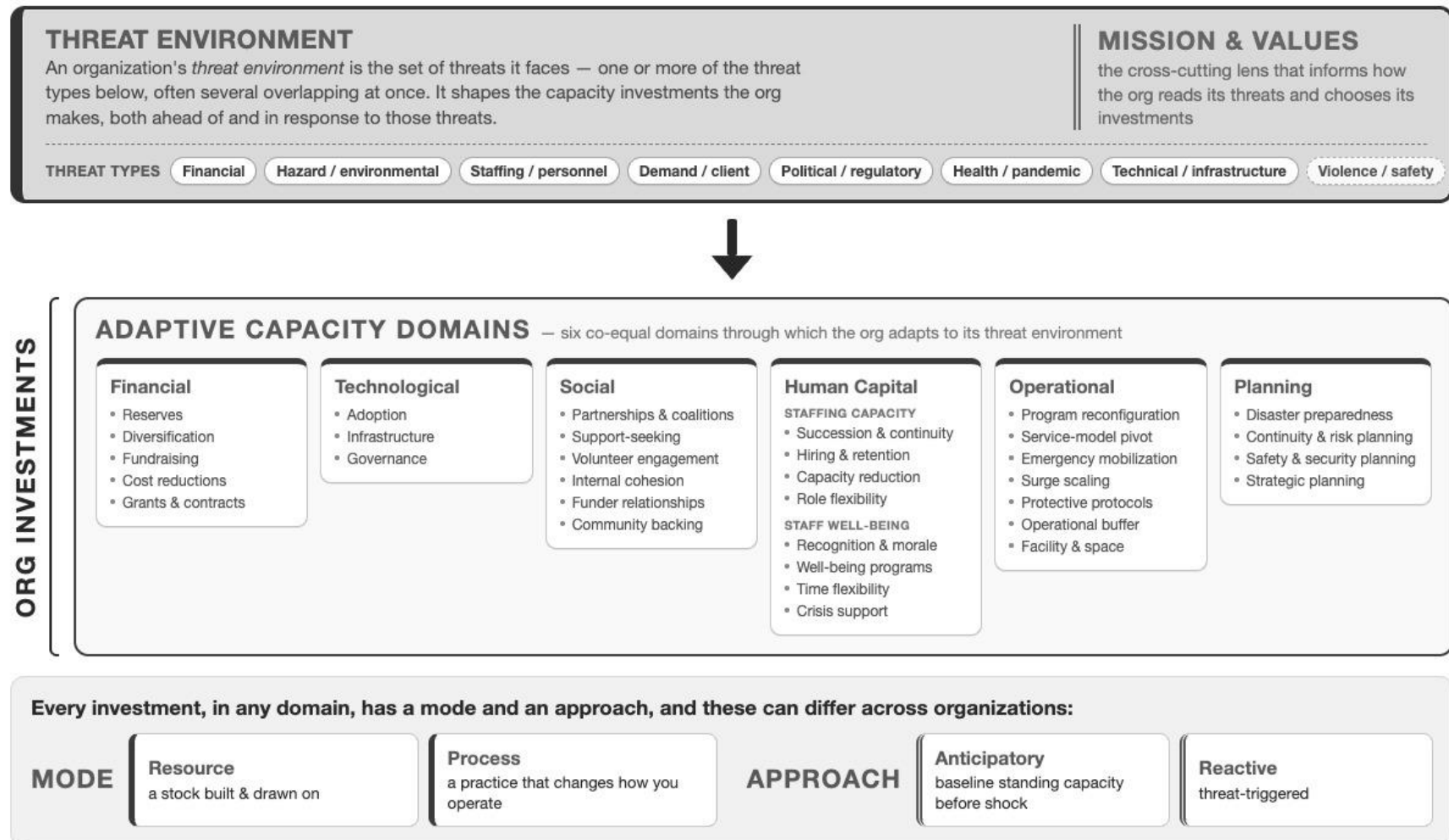


Figure 2. The OR-TIIF is an analytic typology & practitioner planning tool for community-based nonprofits. The 33 indicators are grounded in 326 threat-response episodes across 50 CBOs.

4. Findings

I present the findings in the order the analysis developed. Each structural feature of the OR-TIIF was determined by a specific pattern in the episodes. Throughout, the unit of analysis is the threat-response episode, with 326 episodes across 50 organizations and 33 final indicators. Investment coding is an overlay on episode coding, so domain counts do not sum to episode counts. Full per-cell counts are reported in the figures and tables.

4.1. CBOs Face Diverse and Cumulative Threats

The threat environment described by organizational leaders was broader than the discrete natural-hazard frame and more cumulative than event-centered models assume (Figure 3). Financial threats are the largest category at 27 percent of episodes, and political and regulatory threats add another 12 percent, so financial and political pressure together account for two of every five episodes. Hazard-environmental threats, the category around which much resilience planning is organized, account for 16 percent.

The remaining episodes are distributed across staffing and demand (13% each), health and pandemic disruption (10%), technical disruption (7%), and the small violence and safety category. Leaders drew this contrast themselves, routinely ranking chronic political and economic pressure above the named hazards their regions are known for. One leader whose community had just been through an unprecedented wildfire put it this way:

We have ICE raids impacting the area, and we have a lot of staff who are different ethnicities. We have a broad community of people here who are undocumented, or going through processes of getting documentation, and in some ways, that's a much more stressful kind of ongoing event than the [fire]. (West, human services organization)

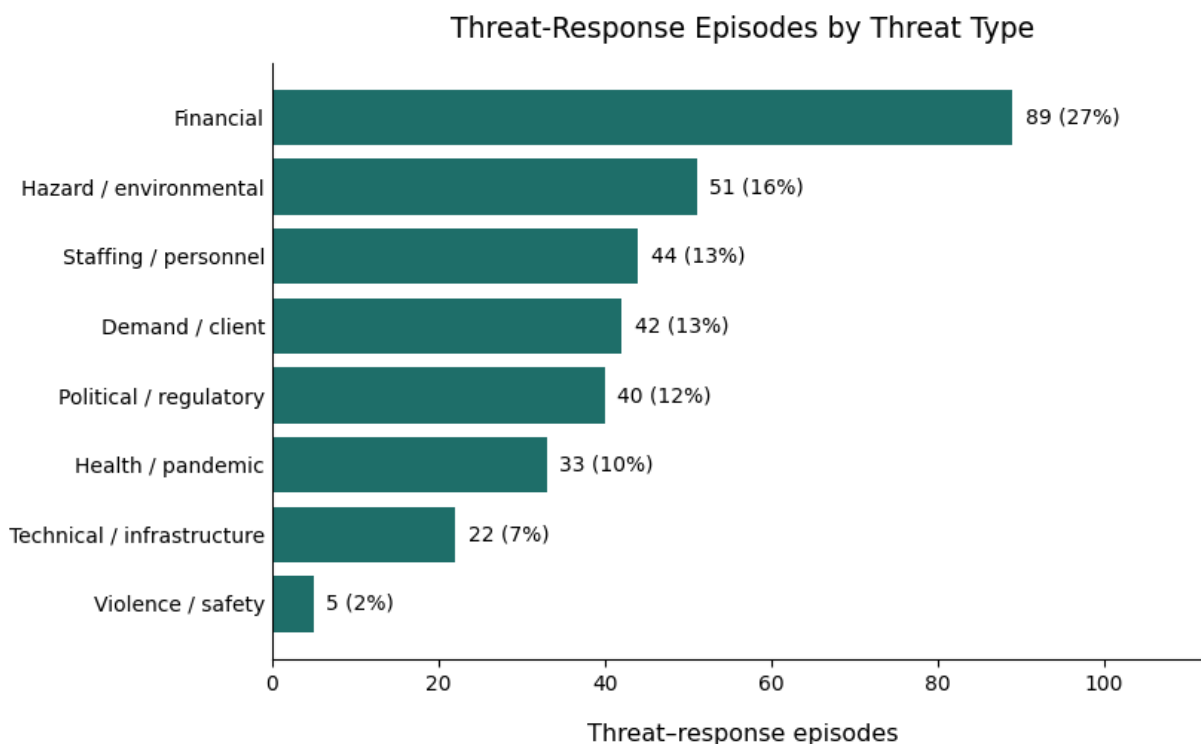


Figure 3. Counts are threat-response episodes per threat-type, not organizations. Financial and political/regulatory pressure together account for two of every five coded episodes; hazard/environmental threats account for roughly one in six.

This multi-threat pattern appears within organizations as well as across the sample. When asked to characterize the threats CBOs faced, nearly every leader named several forms of disruption as consequential and often interacting. But naming multiple threats says nothing about how they unfolded, so I coded each interview for the temporal relationship among them.

Leaders divided into rough thirds. Of the 50 leaders, 19 described threats as actively compounding, overlapping within the same period or arriving in rapid succession before prior disruptions had been resolved. Another 15 described something different, not a pile-up of discrete shocks but a chronic unresolved condition of scarcity, political pressure, or organizational strain. The remaining 16 described threats as discrete and sequential. Roughly two-thirds, then, narrated something other than a bounded single crisis. This changes the object

that a CBO resilience framework must explain, and it is the empirical basis for treating the threat environment rather than any particular event as the framework's contextual frame. Several leaders went further and extended the word “disaster” itself beyond declared events to the chronic emergencies their clients face daily: “The disasters that we see folks facing is living paycheck to paycheck and losing their housing, and that's a real disaster in real time” (West, human services organization). This broader understanding of disaster has precedent in disaster research. Chronic poverty and housing precarity shape how low-income communities experience discrete events (Fothergill and Peek 2004), and service providers have long described their everyday operations in disaster terms (Vickery 2015).

4.2. Threats Often Prompt Matching Capacity Investments

The previous section established that most CBOs face a multi-front threat environment. The next question is whether different threats call forth different kinds of resilience investment. Cross-tabulating episodes by threat type and investment domain shows a clear matching pattern, in which organizations invest in the capacity most directly pressured by the threat (Figure 4). The financial diagonal is the clearest example. Financial investment is the dominant response to financial threat, appearing in 57 percent of financial-threat episodes. Technical/Infrastructure threats show the same pattern. Two-thirds of technical-threat episodes include a technological investment, while technological investments appear at much lower rates elsewhere (0–10%). Technology therefore functions as a strongly threat-coupled lever, not a general resilience resource. Staffing threats are also answered in kind, through the two subdimensions of Human Capital: staffing capacity (hiring, retention, succession, and restructuring) and staff well-being (recognition, flexibility, and crisis support). About two-thirds of staffing-threat episodes include at least one of these forms of investment.

Capacity Investments by Threat Type

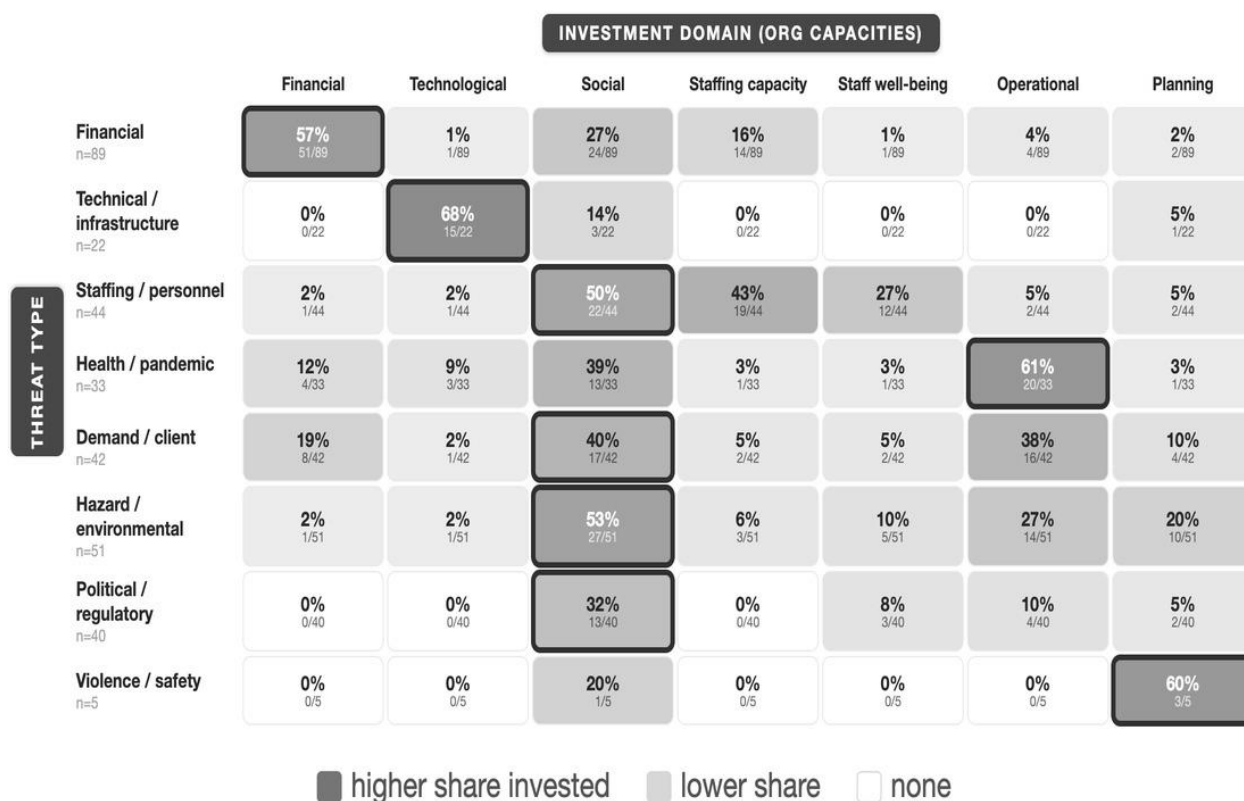


Figure 4. The cells show the share of episodes within each threat environment that included investment in each organizational capacity domain. Darker shading indicates a higher share of episodes, and the outlined boxes mark the largest domain response within each threat row. Rows are ordered to foreground diagonal-like matches between threats and capacity domains, such as financial threats calling forth financial investments, technical/infrastructure threats calling forth technological investments, and staffing/personnel threats calling forth staffing and well-being investments. Because investments are overlay-coded, one episode may appear in multiple domains and row percentages do not sum to 100. Staffing capacity and staff well-being appear here as the two coding dimensions that the final framework combines under Human Capital, so the figure shows seven columns for six framework domains.

This matching pattern is not only visible in the descriptive matrix. As a check on the cross-tabulated patterns, I estimated cluster-robust logistic models on the same 326 episodes, each predicting whether an episode included an investment in a given capacity domain. A financial threat was associated with roughly twenty-one times the odds of financial investment (OR = 21.38; 95% CI [12.37, 36.93]; $p < .001$), and a hazard/environmental threat with

roughly four times the odds of planning investment (OR = 4.23; 95% CI [1.91, 9.35]; $p < .001$). These estimates should not be read causally, but they support the descriptive claim that some threats are tightly coupled to particular investment domains. The diagonal, however, is not universal, and its exceptions are analytically more illuminating than the pattern itself.

4.3. Health and Demand Threats Prompt Operational Change

Some threats do not deplete a single replaceable investment stock. They are absorbed instead through operational process change. A pandemic, for example, does not simply drain money, staff, or technology. It disrupts how the organization delivers services. In these episodes, organizations invest operationally, with 61 percent of health/pandemic episodes including an operational investment, overwhelmingly through service-model pivots and protective protocols (Figure 4). Demand/client threats behave similarly, though less sharply (at 38%) as organizations scale, reconfigure intake, and redesign workflows to absorb more or different demand than their original model anticipated. One leader described this absorption in real time during the 2025 SNAP pause:

That one, I didn't even ask permission from my board. I just said we are going to extend services ... people could come every week ... probably six additional visits for people. And when we did the numbers, about 80 percent of the people who used those extra visits had been in before but didn't have any more visits. (South, human services organization)

4.4. Planning Centers on Forecastable Threats

Planning follows a different pattern, concentrating where threats are forecastable. It appears in 20 percent of *hazard/environmental* episodes, compared with 0–10 percent of most others. Organizations plan more readily for disruptions they can imagine recurring in recognizable form, such as storms, floods, and facility emergencies. Novel shocks like COVID-

19 were absorbed through operational pivoting at onset. Leaders who did plan were clear that plans are starting points, not fixed:

Our plan is 100 percent adaptable ... the biggest thing we've learned about planning is, like we used to say in the army, no plan survives first contact. (Northeast, faith-based community organization)

I've always said the one thing you cannot predict is how your staff members will be able to respond. Some of them were personally affected. Some of them were traumatized and couldn't function. ... You may say, well, this person is going to do this, and this person is going to do that, when you have no idea [whether] they will have the capability, or even the mindset, to continue to do that. (South, community development organization)

This contrast is what forced the mode axis. Financial, technological, and some human-capital investments behave like stocks. Operational and planning investments behave more like practices, meaning routines that are enacted, changed, formalized, or improvised. Mode therefore cannot be a structural level in the framework, because every domain contains both. What differs is each domain's composition, which the mode tag makes visible as a gradient running from the most resource-heavy domains (technological, social, financial) to the fully process-heavy ones (planning, staff well-being).

4.5. Social Capacity Functions as Standing Infrastructure

Social capacity is the most common investment domain in the corpus, appearing in 120 of 326 episodes, and it behaves unlike the threat-coupled domains. It appears in every threat row, ranging from 14 percent of technical episodes to 53 percent of hazard episodes, yet it has no diagonal. There is no single “social threat” to which it is tightly coupled (Figure 5). Social investments are also disproportionately anticipatory, with 37 percent being standing capacities activated by the threat, not built because of it. Relational capacity therefore functions as standing infrastructure, not a reactive lever.

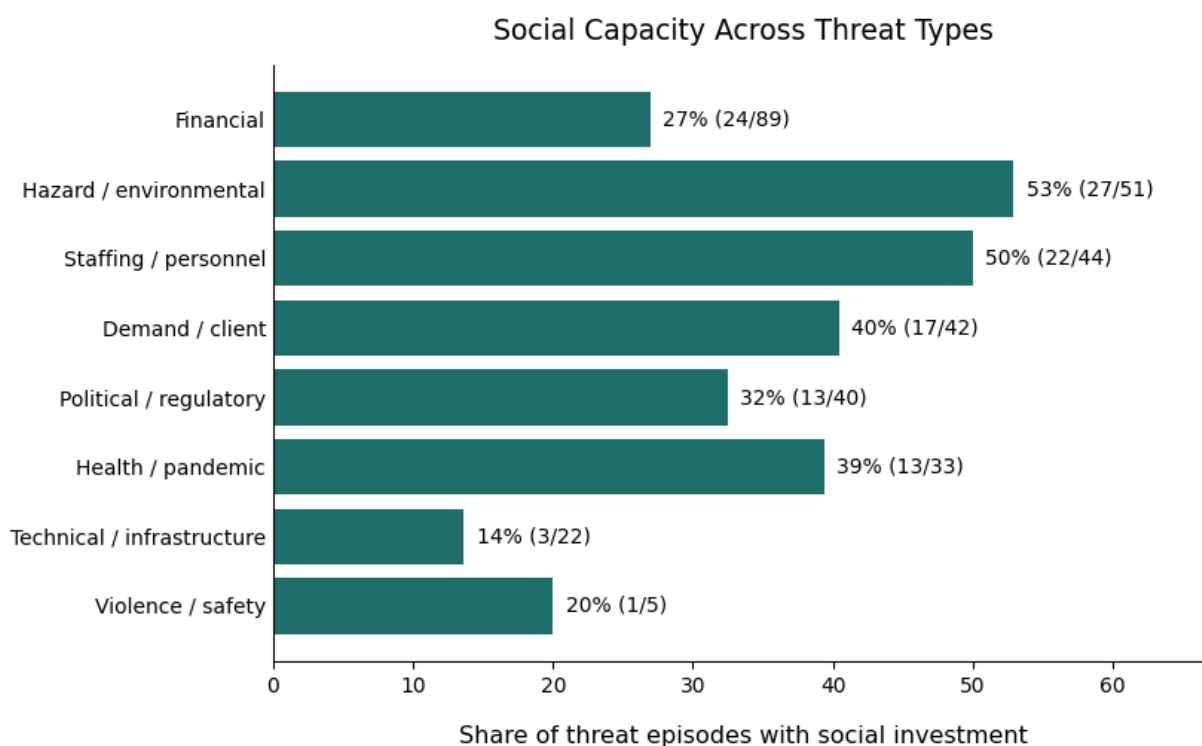


Figure 5. Social investment appears across all threat types.

This is one of the paper's central theoretical findings. Organizations draw on partners, coalitions, volunteers, funders, and community trust across nearly every kind of disruption. These ties precede the named threat, travel across threat types, and make other responses possible without appearing as a discrete crisis action. Leaders described this connective layer as sustaining community trust and building partnerships in place of crisis-specific planning:

I think rather than us stepping back and saying, 'what's our plan?' Or 'how can we be ready?' It's more like, we know our lane. Let's still continue to be really good at this and really reliable ... build that trust with people, so that when there's a natural disaster or there are threats, at a political level, to these benefits folks access. They know they can come to us like they already know our name. They already know we're trustworthy. (Northeast, food-security advocacy organization)

You know that's a huge part of my leadership. I believe strongly in building partnerships, building collaborations, and building connections ... At the end of the day, we all need each other, even if it is just for benchmarking, for moral support. So yes, I am part of a couple of collaboratives, a few coalitions of other leaders in the nonprofit sector that meet regularly to brainstorm about how to better respond to the current challenges. And that is extremely important. (South, senior services)

Business and management frameworks recognize networks and stakeholder ties, but treat them as one capability among many. Nonprofit frameworks bring relationships closer to the center, though within a single crisis or as one item in a resource list. The episode data show a sharper distinction and explain why Social and Human Capital had to be separated. Staffing threats call forth human-capital investment in matching form. Social capacity spreads across threats. Merging the two would bury a real difference between a capacity that answers its own threat and one that underwrites response across the whole environment.

4.6. Political and Regulatory Threats Prompt Tactics, Not Capacity Investment

Political and regulatory threats are the boundary case. They prompt less capacity investment than any other threat type, and frequently none at all. A majority of political/regulatory episodes (58%) contain no capacity-domain investment, compared with 12–26 percent for every other threat type, and none of the episodes produce financial, technological, or staffing-capacity investment. The only substantial capacity-domain response is social investment, at 32 percent of episodes (Figure 6). This does not mean political threats are unimportant. It means they operate outside investment logic. A hostile regulatory shift cannot be answered by staff training. What these episodes, and others like them, call forth instead are tactics, such as organizing, coalition building, and public positioning, which are responses but not investments in internal capacity.

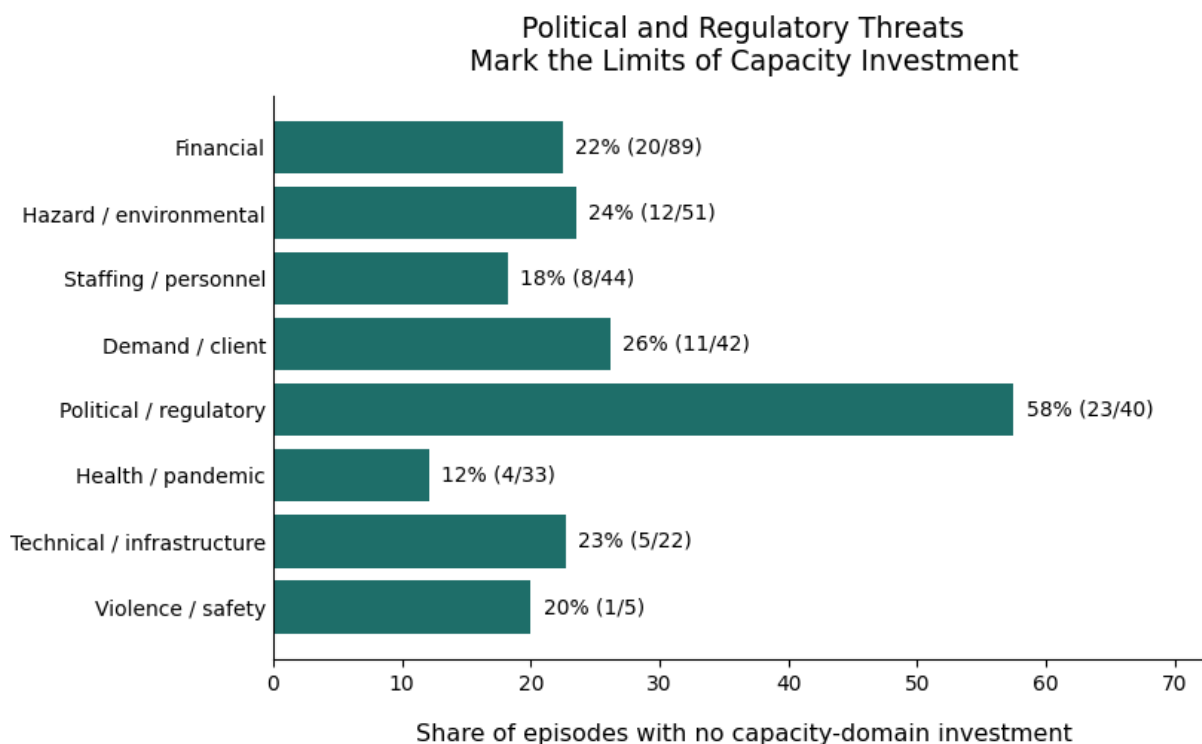


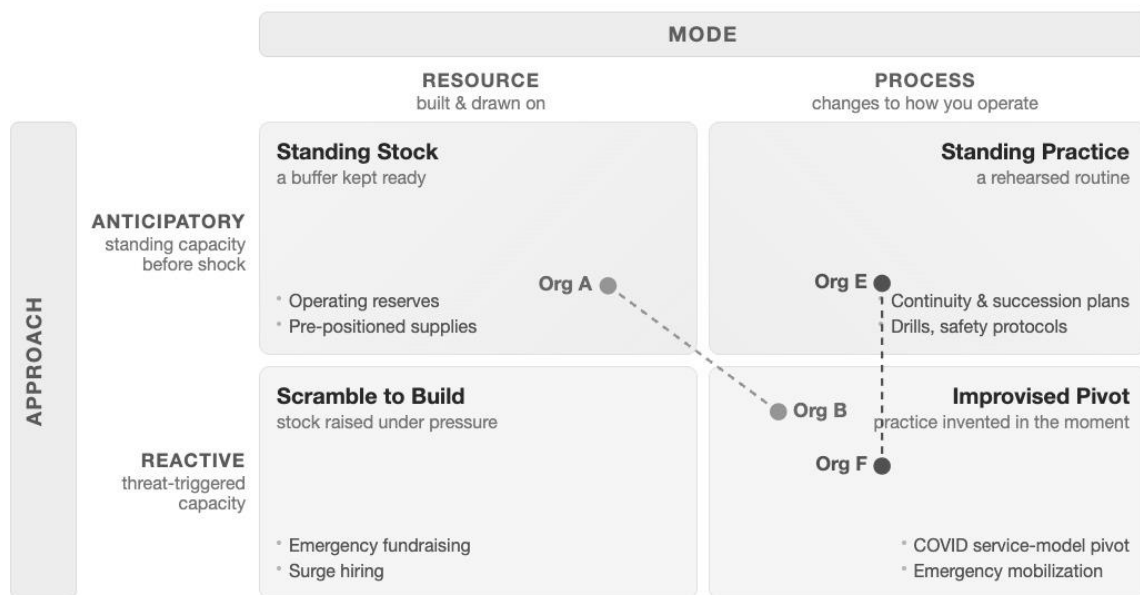
Figure 6. Political/regulatory episodes have the highest rate of zero capacity-domain investment, not because organizations do nothing, but because their responses often take a tactical form.

For this reason, political threats belong in the framework, but in a bounded way. The OR-TIIF is not a full tactics typology. What political/regulatory threats clarify is the framework's scope. The unit of analysis is capacity investment, so when threats routinely call forth tactics instead, the framework should mark that boundary instead of absorbing tactics into the capacity structure. The political exception also carries a practical implication. Funders and boards ask organizations to become more resilient by strengthening internal capacity, which is appropriate for many threats. However, political and regulatory threats can break that premise. An organization facing these threats may need unrestricted support or legal or advocacy capacity. The appropriate response may sit outside the organization's internal capacities.

4.7. Mode and Approach Produce Four Investment Postures

The final OR-TIIF crosses each investment domain with two axes. *Mode* distinguishes resource stocks from operating practices, and *approach* distinguishes anticipatory capacity from reactive capacity. Together they yield four investment postures. This 2×2 is where the framework becomes most useful diagnostically (Figure 7 and Table 2). An *anticipatory resource* is a standing stock, such as reserves, physical supplies, data infrastructure, or relationships held before the threat. An *anticipatory process* is a standing practice, such as safety protocols, succession plans or well-being practices. A *reactive resource* is a stock built under pressure, such as emergency fundraising, urgent hiring, or rapid technology acquisition. A *reactive process* is an improvised pivot, such as a service-model shift, an emergency mobilization, or a change to how the organization prioritizes need.

Four Investment Postures by Mode and Approach



EXAMPLE SCENARIOS

- **Partnerships:** Org A simply activates a standing coalition (*anticipatory resource*); Org B scrambles to build new partnerships (*reactive process*). A checklist scores both as “Invested in partnerships”; the OR-TIIF tells them apart.
- **A Continuity Plan:** Org E maintains one as standing practice (*anticipatory process*); Org F writes one only after a near-miss (*reactive process*). Same indicator, same mode, different approach.

Figure 7. The 33 framework indicators can be organized by mode (resource vs. process) and approach (anticipatory vs. reactive). The same indicator can sit in different quadrants across organizations and threats. The framework helps characterize not just whether an organization invested, but how, and how deliberately. There is no “correct” investment profile, and the framework does not (yet) show that any posture causally improves outcomes. It is a structured way to see the alignment between an organization's threat environment and its investment posture.

Table 2. Four OR-TIIF Investment Postures

Approach	Mode	Episode Evidence
Anticipatory	Resource	A buffer maintained before the threat (reserves, supplies, data infrastructure, or relationships activated when needed).
Anticipatory	Process	A rehearsed routine already in place (continuity routines, cross-training, succession or well-being practices, safety protocols).
Reactive	Resource	A stock assembled under pressure (emergency fundraising, urgent hiring, rapid technology acquisition).
Reactive	Process	A practice invented or reconfigured in the moment (service-model shifts, emergency mobilization, triage changes).

Investment tags cluster unevenly across the four quadrants. Of the 355 coded investment tags with an approach classification, 257 (72%) were reactive, meaning they were mounted because of a threat instead of standing beforehand (Figure 8). This percentage describes investment tags, not the 326 episodes, because a single episode can contain multiple capacity investment tags. The concentration is unsurprising among small CBOs operating on thin margins, and improvisation under chronic scarcity is not necessarily failure. Leaders described this pattern as a structural condition:

One of our challenges is that we don't have the money that we would love to have in order to be as prepared. So we rely a lot on the ability of staff members to pivot and funders to fund us. We don't have a lot of documentation, like a 40-page document on how we're going to respond in every disaster. (South, human services organization)

Nonprofits' mentality has to shift from the immediate crisis to the future orientation of crises. ... People are just trying to feed the person for the day. They're not thinking of the earthquake that's coming in 50 years, and they don't have the funding to think of that. ... For-profits have the money to put into thinking about the bigger picture. We do not. (West, human services organization)

The exception is staffing/personnel, the only threat type in which anticipatory investments outnumber reactive ones (56%). This pattern is driven by the well-being cluster, suggesting that some human-capital practices are standing capacities. Viewed by investment domain instead of threat type, anticipatory capacity concentrates in Social and Planning, where roughly 37 percent of investments are standing.

Investment Approach by Threat Type

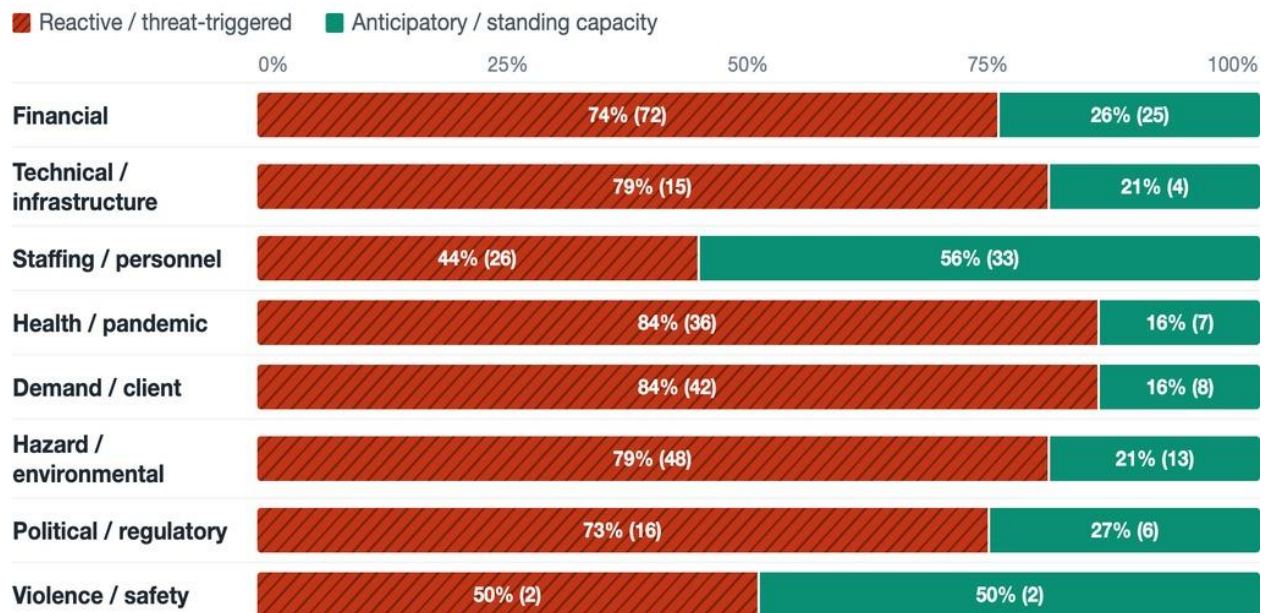


Figure 8. Reactive and anticipatory investment approaches by threat type. The bars show the balance of reactive and anticipatory investments within each threat type. Reactive investments are newly triggered responses mounted because of a threat, while anticipatory investments are standing capacities already in place and activated during the threat. Most threat types are

dominated by reactive investment, but staffing/personnel threats are the exception. In this case, anticipatory investments slightly exceed reactive ones, suggesting that some human-capital capacities, especially staffing and well-being practices, are more likely to preexist the disruption.

The OR-TIIF diagnostic payoff is that the same investment domain can occupy different quadrants across organizations, which a checklist can miss. Two organizations may both “invest in partnerships,” but one activates a coalition cultivated over years:

As far as external factors ... we learn the value of ‘you need to create relationships before disasters happen.’ Flat out, you don't create them within there. You would need to have your contact list. (South, community development organization)

while the other scrambles for allies mid-crisis:

[During COVID] there just quickly became this partnership [with a senior-meals program], which had the ability to bring all these meal packs... the office on aging had 50-plus community centers, and then we had a whole bunch of drivers... So within probably 30 days, we just started piloting that. (South, senior transportation organization)

Additionally, two organizations may both appear well prepared, but the capacities underlying that preparedness can take different forms. One might institutionalize preparedness through a standing planning and accountability process, while another builds durable resource stocks to absorb future shocks. A presence/absence instrument records both as having resilience capacity. The OR-TIIF distinguishes the mode and approach behind that capacity. One food bank built a standing planning practice deliberately over a year:

The first decision we made was that we were not going to use consultants ... it needed ownership and it needed buy-in, and it needed to be developed, therefore, by those that were going to use it. ... We took each of the goals that we identified and said, what would success look like against each of these goals ... and we meet as a leadership team and look at that every month ... We have an organizational scorecard ... that we are held accountable to by our board. (South, food bank)

Another leader described building standing stocks precisely so that future shocks could be absorbed without scrambling:

Risk can be strategic. ... What we're looking to do is buy other properties ... the goal is, whatever property we move into next, we own, so we don't have to worry about anything. If [the organization] does go south, we own the property, we can resell it, we can refinance. (South, food-recovery organization)

This distinction matters because the presence of a formal plan is not the same as being able to absorb disruption. A plan structures action; resource stocks make action possible.

Instruments that record only whether a plan exists can mistake formalization for preparedness and overlook other forms of anticipatory investment. By distinguishing standing processes from standing resources, the OR-TIIF shows not only whether an organization has prepared, but how that preparation is expected to work and what capacity may still be missing. This posture-level reading is the framework's core contribution to analysis and practice.

5. Discussion

5.1. Resilience as Threat-Informed Investment

The OR-TIIF shifts the object of analysis from what capacities an organization has to what it invests in. Existing frameworks ask whether an organization holds resilience-relevant capacities, whether it can adapt to disruption, or whether it can prepare for a specific event. This framework asks what the organization built, replenished, activated, or reconfigured in relation to the differentiated and overlapping threats it has faced. Five contributions follow.

First, the framework operationalizes threat environment as an analytic input. The distinction is not event-specific versus non-event-specific. That contrast is too blunt, because

organizational-resilience scholarship includes both discrete-shock and continuous-adaptation frameworks. The sharper distinction is between environment as background and environment as differentiated input. For CBOs, financial instability, political/regulatory pressure, staffing strain, demand shifts, health disruption, technical failure, and natural hazards are not interchangeable instances of “disruption.” They are different threats with different investment logics, and treating hazard as the default case would misclassify most of the disruption in this corpus.

Second, the framework offers a CBO-specific correction to business and management resilience research. Dominant frameworks supply useful language for capability, continuity, learning, and adaptation, but the settings they were built from make performance, competitiveness, and operational continuity the outcomes of interest. CBOs face a different resilience problem. They must sustain their mission under restricted funding, thin margins, community accountability, staff strain, and dependence on funders and regulators. The OR-TIIF therefore treats mission and values as the interpretive lens, relational capacity as standing infrastructure, and the threat environment as part of the operating model instead of an occasional external disturbance.

Third, the framework extends nonprofit-resilience research by explaining how different threats lead to different investments. Financial, technical or infrastructure, and staffing threats usually prompt organizations to strengthen the same capacity area. Health and demand shocks are handled mainly through changes in operations. Planning is most common when threats are predictable, while social capacity supports organizations across all threat types. Political and regulatory threats often prompt advocacy, coalition defense, and mission-based tactics when internal investment cannot address the source of the threat. Politically driven funding cuts or freezes are classified as financial threats because they require internal financial responses.

Together, these patterns show that organizations respond by replenishing resources, changing operations, planning ahead, activating relationships, or using tactics outside internal capacity building.

Fourth, social capacity follows a different pattern from the other investment domains. It is the most common domain and appears across every type of threat without being tied to any one of them. This finding supports the paper's broader argument that relational capacity is central to organizational resilience. Relationships function differently from financial, technological, and staffing capacity. They are less likely to be built in response to a specific threat and more likely to exist as standing infrastructure that organizations draw on across disruptions.

Fifth, the framework treats anticipation as a feature of investments across domains. Planning can occur after a disruption, while social and financial capacity can be built in advance. A financial investment, for example, may take the form of a standing reserve or emergency fundraising. Applying this temporal distinction to every investment shows when capacity was built and better reflects the patterns in the threat-response episodes.

5.2. Political Threats and the Limits of Internal Capacity

Political and regulatory threats mark the boundaries of the OR-TIIF's capacity-investment logic. A framework that explains every response by continually expanding its categories can quickly become too broad to be useful. The OR-TIIF therefore separates investments in internal adaptive capacity from other actions organizations take to protect their missions. In these episodes, organizations often rely on advocacy or public messaging. These actions can be essential to survival, yet they do not necessarily build internal capacity. Treating

them as a separate tactical layer keeps the framework analytically focused and identifies political tactics as a distinct area for future analysis. The OR-TIIF classifies politically driven grant freezes and funding cuts as financial threats because organizations respond through internal financial decisions.

5.3. The OR-TIIF as a Diagnostic Tool

For practitioners, the OR-TIIF works best as a structured diagnostic tool. It helps organizations identify the threats they have faced, the capacities they relied on, where they repeatedly improvised, and which capacities were depleted without being replenished. It also shows whether the resulting profile reflects deliberate choices or constraints that accumulated over time. The framework gives organizations language for resilience work they already perform, including relationship maintenance, staff support, program adjustment, and funder communication.

For funders, the framework distinguishes threats that organizations can address through internal capacity-building from those that require changes in funding structures or policy conditions. A major loss of grant funding or shifting regulation cannot be solved by asking a CBO to plan better. The framework also shows why funders should support standing capacity before a crisis occurs. Preparedness and prevention are difficult to fund because their success is often invisible. A leader with disaster-relief experience described this challenge directly:

It's not fun or sexy to fund or plan for a thing that never happens, or to successfully mitigate a thing, and then it's not newsworthy. ... It's really hard to make a compelling narrative for why that's important, or why that's cheaper. People obviously understand that it potentially alleviates suffering, but how do you prove it? (West, human services organization)

The OR-TIIF complements continuity plans and scenario exercises. Those tools help organizations activate networks and adjust operations when a known hazard occurs. The OR-TIIF can be used before or alongside them to show which resources and processes an organization has relied on across disruptions and where improvisation is substituting for resourced standing capacity.

5.4. Limitations

This study's claims should be interpreted within the scope of the research. The purposive sample was designed to capture variation across regions, organizational characteristics, and threat environments. It does not estimate the prevalence of these patterns across the U.S. CBO sector. The sample is also limited to organizations that were operating during recruitment and does not investigate whether organizations that closed followed different investment patterns. Participants reflected those who had enough time and capacity to participate. Organizations that were too stretched to respond are not represented. These accounts might miss standing capacities that kept threats from becoming salient or fail to capture the perspectives of frontline staff, board members, or organizational partners. Episode counts describe patterns within this corpus. The model-based check uses clustered standard errors to account for episodes nested within organizations. Neither the counts nor the models provide population estimates.

The OR-TIIF has not been validated against organizational outcomes or tested as a practitioner instrument. It identifies investment profiles without establishing that any specific profile improves continuity or reduces depletion. All coding was completed and verified by one researcher, so the study cannot assess intercoder agreement. Repeated full-corpus review and line-by-line verification strengthen consistency without replacing independent coding. The

political and regulatory context of the 2025–2026 data-collection period also shaped the threats leaders described. This historical specificity is part of the paper’s contribution. It also warrants testing the framework during different periods and across other sectors and national contexts.

5.5. Future Research

The OR-TIIF characterizes how organizations invest in resilience capacity. It does not establish whether one investment posture produces better outcomes than another. Future empirical research should consider linking investment profiles to measures of depletion, operational continuity, and sustained mission delivery. This would show whether particular profiles are associated with stronger organizational conditions over time. Research should also examine the tactics organizations use when threats cannot be addressed through internal capacity-building. This paper argues that political and regulatory threats may offer a clear starting point, calling forth responses that fall partly outside the OR-TIIF’s capacity domains and warrant analysis in their own right. Finally, the framework should also be tested in practice. A facilitated OR-TIIF protocol could be piloted with CBOs and funders to assess whether the diagnostic process changes how participants identify threats, prioritize investments, communicate funding needs, and direct future resilience work.

6. Conclusion

CBOs operate within differentiated threat environments that cannot be reduced to generalized adversity. In this study, those environments extended beyond natural hazards to include financial, political, staffing, demand, health, technical, and safety pressures. The investments that organizations made followed clear patterns. Financial, technical, and staffing threats often prompted investment in the corresponding capacity. Health and demand shocks

were absorbed mainly through operational change, while planning concentrated around forecastable hazards. Social capacity operated across threat types as standing resilience infrastructure. Political and regulatory threats showed the limits of internal capacity investment and the framework itself.

The OR-TIIF makes these patterns visible by treating the threat environment as an empirical input. It organizes six adaptive-capacity domains by mode and approach to produce an investment profile. The framework's contribution is that it shows how an organization's investments align with the threats it faces and where internal capacity-building is insufficient. The central practical question is not simply, "Are we resilient?" or "Are we prepared for X?" It is, "What do we have on hand, what have we drawn down, what have we rebuilt, and is this the posture we want to carry forward?"

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Paper 3: The Hidden Costs of Persistence in Community-Based Organizations

Abstract

Nonprofit organizations are often described as a resilient sector because many continue operating through chronic resource constraints and repeated disruption (Young 2022; Chen et al. 2024). Continued operation, however, does not show what condition an organization is in or what resources it draws down to keep its doors open. Drawing on interviews with leaders of 50 community-based organizations (CBOs) across 28 U.S. states, conducted between December 2025 and July 2026, I develop a four-category typology of operational condition: thriving, recovering, strained continuity, and depleted continuity. All 50 organizations were open at the time of interview. While their finances, staffing, and operations varied, this study finds that relationships and community embeddedness helped organizations remain open across all four operational conditions. The conditions differed along the lines of whether those strengths were paired with financial buffers, adequate staffing, durable systems, and time to recover. Organizations entered a state of depleted continuity when continued service depended on spending down reserves, narrowing mission scope, exhausting staff, postponing maintenance or system upgrades, or relying on leaders' unpaid labor, personal funds, and health. While leaders often described these costs in detail, their overall assessments still portrayed the organization as managing or thriving. I argue that CBO resilience should be assessed through operational condition. This approach shows what organizations consume to remain open and identifies the types of internal supports needed to sustain their work.

Keywords: organizational resilience; nonprofit organizations; community-based organizations; nonprofit resilience; relational support; organizational depletion; thriving

1. Introduction

In 2025 and 2026, many community-based organizations (CBOs) lost federal funding as demand for their services increased. Political pressure, regulatory changes, and local hazards added further strain (Grundhoefer et al. 2026). Leaders in this study described canceled grants, expected funding losses, and demand increases tied to benefit reductions, including changes to SNAP. Many were uncertain if they would be able to meet growing community needs. A representative of a national nonprofit finance and consulting organization described how these pressures interact with other forms of disruption:

[In addition to the loss of federal funding to nonprofits and the people they serve] ... you think about all of the other things that are outside of a funding dynamic, like a natural disaster or a man-made disaster that affects the community...and you get these compounding effects...and it's when you're dealing with trying to stay open...you're going to focus on today and tomorrow. So often the mindset that nonprofit workers and leaders have had to take in order to survive in this sector has been, "how do we make this work with what we have?" Not necessarily, "what would it take to do this right?" and by right I mean like sustainably with just wages and appropriate resourcing for meeting the needs as they currently stand. When you're constantly in the mindset of "How can I make this work?" self-sacrifice comes in so quickly, especially because this is a sector where people are driven by mission.⁵

In this environment, discussion across the sector centered on which nonprofits would remain open and which would close (Ludden 2026). This paper asks a different question: What condition are organizations in as they continue operating? Every organization in the sample was open at the time of interview. All had endured earlier disruptions, and several had operated for

⁵ This quote is from a personal communication with a representative of a national nonprofit finance and consulting organization. The conversation provided broader sectoral context for the patterns identified in the study but was not included in the formal dataset or analysis.

decades. Continued operation therefore could not distinguish organizations that preserved their capacity from those that remained open by consuming resources they could not replace.

Among the 50 organizations analyzed in this paper, persistence took four forms. *Thriving* organizations covered their operations, maintained or rebuilt reserves, and did not steadily consume core capacity. *Recovering* organizations were rebuilding after earlier depletion. Organizations in *strained continuity* faced tight finances or thin staffing without sustained losses they could not replenish. Organizations in *depleted continuity* remained open by spending down their reserves, reducing programs, exhausting staff, or putting off needed repairs and system upgrades. Leaders also covered organizational gaps through unpaid labor, personal funds, and costs to their health. The paper addresses two questions:

1. Among CBOs that continue operating through repeated pressures, what allows some organizations to preserve or rebuild internal capacity while others draw down staff, reserves, mission scope, infrastructure, or leadership capacity?
2. How do leaders' accounts and broad self-reports shape what becomes visible or obscured about operational condition?

Relationships helped organizations in every condition remain open. Community ties often produced money, volunteers, in-kind goods, shared services, information, or advocacy support. That usable support was common in thriving and depleted organizations. The difference was what the support protected or rebuilt. In thriving organizations, it helped preserve reserves, staffing, systems, or recovery time. In depleted organizations, immediate demand consumed it.

Most thriving organizations were *lean*, meaning they had little spare capacity. Among the 19 thriving organizations, 17 had lean capacity. What distinguished them was that pressure did

not steadily consume their reserves, staff, infrastructure, or mission scope. They had modest buffers, invested in staff and operations, and had time to recover. Recovering organizations had also experienced depletion, though their condition was improving.

These differences were not always visible in leaders' overall assessments of how well their organizations were doing. Leaders described exhaustion, unpaid labor, deferred work, and financial strain in detail. Only 2 of the 13 leaders in depleted continuity described their organizations as struggling. Another 9 described them as managing, and 2 described them as thriving. These judgments largely focused on whether the organization continued serving its community, fulfilling its mission, and maintaining trust. The operational condition coding used evidence about reserves, staffing, infrastructure, deferred work, and unpaid labor to determine whether continued service was preserving or depleting the organization's internal capacity. Leaders could therefore describe serious internal strain while still viewing the organization as managing or thriving. They were assessing whether the work continued; the coding in this study assessed what the organization was consuming to keep it going.

Section 2 reviews why existing research often captures whether organizations survive or recover without showing the condition in which they continue operating. Section 3 describes the sample and classification strategy. Section 4 presents the typology and explains what distinguishes the four conditions. The paper closes by considering what condition-level analysis changes for resilience theory, nonprofit research, and funder practice.

2. Background

2.1. Resilience as a Capability, Process, Outcome, and Condition

Organizational resilience has been defined in several ways. Scholars most commonly treat it as a capability, a process, or an outcome (Duchek 2020; Hillmann and Guenther 2021). Each perspective explains a different part of how organizations prepare for, respond to, and emerge from disruption.

Capability-based accounts focus on the resources and routines organizations have available before disruption. These capabilities include financial and staffing buffers, planning practices, institutional knowledge, and access to technological and relational resources (Sutcliffe and Vogus 2003; Duchek 2020; Barasa, Mbau, and Gilson 2018). Duchek's (2020) model treats resilience as a meta-capability composed of anticipation, coping, and adaptation. This perspective helps explain why some organizations enter a disruption better prepared than others. Its practical application is that resilience can be diagnosable in advance. If resilience is a capability, then researchers and practitioners can ask what an organization has on hand before the shock.

Process-oriented accounts focus on how organizations respond as disruption unfolds. They emphasize sensemaking, improvisation, coordination, learning, and adaptation (Weick 1993; Williams et al. 2017; Duchek 2020). This framing is important because organizational resilience rarely operates as a stable trait. The same resource can support different responses depending on how and when it is used. Slack resources, for example, can help an organization maintain operations, change its service model, or pursue a new opportunity (Conz et al. 2023). Process accounts therefore examine how organizations mobilize and reconfigure capacity under pressure.

Outcome-based accounts infer resilience from observable results. These results can include continued operation, maintained performance, recovery, transformation, or movement toward a new organizational state (Hillmann and Guenther 2021; Hernes et al. 2025). Recent work has moved beyond a simple return to pre-disruption conditions, showing that organizations often adapt toward uncertain futures instead of returning to earlier conditions (Hernes et al. 2025). Hepfer and Lawrence (2022) also distinguish functional, operational, and strategic resilience, showing that continuity in one area can coexist with vulnerability elsewhere in the organization.

These perspectives capture important dimensions of resilience, but do not fully capture the condition in which an organization continues operating. A CBO can adapt effectively and stay open while exhausting staff, spending reserves, weakening infrastructure, or reducing program scope. In other words, resilience measured as capability, process, or outcome can still miss the costs of persistence. This problem is especially important for community-based organizations (CBOs) whose missions often compel them to remain present even when demand exceeds available resources. Remaining open does not show whether the organization is preserving its capacity, rebuilding it, or consuming resources it cannot replace.

2.2. Financial Health and Operational Condition

Research on nonprofit vulnerability has largely examined whether organizations are financially positioned to withstand shocks and avoid closure. Tuckman and Chang (1991) defined a financially vulnerable nonprofit as one likely to reduce services following a financial shock. Their framework identified inadequate equity, concentrated revenue, low administrative spending, and weak operating margins as potential indicators of vulnerability. Later studies

extended this approach through financial ratios, Form 990 data, net assets, program expenditures, nonfiling, and organizational closure (Greenlee and Trussel 2000; Hager 2001; Trussel 2002; Keating et al. 2005; Dayson 2013). This literature established the importance of financial position. Organizations need reliable revenue and some capacity to absorb interruption to maintain staff, programs, facilities, technology, and administration.

More recent research examines financial resilience and recovery. Studies of the Great Recession, Hurricane Katrina, COVID-19, and state budget crises identify several influences on nonprofit continuity and recovery. These include reserves, equity, funding relationships, and revenue structure (Lin and Wang 2016; Searing 2018; Kim and Mason 2020; Chen 2021; Searing, Wiley, and Young 2021). Kim and Mason (2020), for example, find that nonprofits with larger operating reserves were less likely to reduce hours, lose staff, or experience supply problems during the early months of COVID-19. Chen's (2021) study of nonprofits after Hurricane Katrina similarly shows that financial recovery can take years and that the factors associated with financial resilience are not identical to those associated with financial vulnerability. Searing (2018) further demonstrates that recovery strategies depend on the form of vulnerability an organization faces. Together, this work shows that financial buffers shape whether nonprofits can maintain operations and how much room they have to recover. It says less about the condition of the staff, systems, and routines that make continued operation possible.

Financial indicators capture only part of what contributes to organizational condition. Nonprofit financial health includes liquidity, solvency, margins, reserves, debt, and net assets, and these measures do not describe the same underlying state (Prentice 2016). Administrative records document revenue, expenses, assets, liabilities, and program spending. They do not

directly show staff exhaustion, leadership burden, informal labor, deferred maintenance, or weakening routines. An organization can remain financially viable while operating with worn-down staff, outdated systems, fragile routines, or no time to recover between disruptions.

The meaning of financial indicators also depends on organizational context. Revenue diversification is often treated as protective because it reduces dependence on a single source. Frumkin and Keating (2011) show that revenue concentration can also create administrative and fundraising efficiencies, even as it increases exposure to financial swings. Lin and Wang (2016) find that diversification can intensify short-term fiscal stress during severe crises. No single financial profile therefore represents resilience across all nonprofits. Its meaning depends on the organization's mission, funding model, service responsibilities, and operating environment.

Closure presents a related measurement problem. Nonprofits can merge, stop filing, reduce services, change mission, or remain legally active while operating at a much lower level (Hager 2001; Dayson 2013; Searing, Wiley, and Young 2021). Continued operation also does not show whether the capacities supporting the organization remain intact. Financial viability and persistence are therefore important indicators, though neither fully describes the state of the organization. A condition-level approach asks whether continued operation is supported by resources that can be maintained and replenished, or sustained through ongoing organizational depletion.

2.3. Relational Support and CBO Persistence

Relationships are central to CBO resilience because much of their work depends on resources and coordination distributed across networks. Disaster and community-resilience research shows that trust, social ties, community embeddedness, and organizational networks

support response and recovery (Aldrich 2012; Aldrich and Meyer 2015; Aldrich, Page-Tan, and Fraser 2018). Relationships with residents, peer organizations, funders, volunteers, public agencies, and local leaders help CBOs identify needs, mobilize resources, and maintain legitimacy. These relationships are not peripheral to organizational capacity; they are part of how everyday work gets done.

Research on organizational networks after disasters also shows that timing matters. Doerfel, Chewning, and Lai (2013) find that recovery after Hurricane Katrina depended heavily on relationships established before the disaster. Their study suggests that useful relational support often develops before disruption and can then be activated under pressure. Organizations can form new partnerships during a crisis, though they should not assume that trust and coordination will emerge when they are suddenly needed.

Relationships also provide different forms of support. Han and Piercy's (2026) study of post-COVID nonprofit networks links bridging positions to organizational resilience and closer network positions to adaptive capacity. Different network structures therefore appear to support different functions. Some ties provide access to new information and resources. Others support coordination, shared routines, and problem-solving. Their value depends on the organization's position in the network and the resources that move through its ties.

The same literature also cautions against treating social capital as uniformly protective. Aldrich, Page-Tan, and Fraser (2018) describe social capital as a "Janus-faced" resource because bonding, bridging, and linking ties can produce different and sometimes unequal recovery trajectories. Bonding ties may provide trust, mutual aid, and rapid in-group support, but they can also concentrate resources within already connected groups. Bridging and linking ties may connect organizations and communities to outside resources and decision-makers, but access to

those ties is uneven (Aldrich, Page-Tan, and Fraser 2018). The implication is that social capital can help some organizations and communities recover while leaving others with weaker access to the networks through which resources, information, and institutional support move.

This unevenness is especially visible among small and community-rooted nonprofits. Chandrasekhar, García, and Khajehei's (2022) study of nonprofits in Puerto Rico after Hurricanes Irma and Maria shows that small nonprofits were locally connected and important to recovery planning, but had lower access to post-disaster grant funding and attended fewer post-disaster networking events and workshops than medium and large nonprofits. The authors argue that small nonprofits often have strong community knowledge and local legitimacy, yet may lack the staff capacity, grantsmanship, technical assistance, and institutional access needed to participate fully in formal recovery systems (Chandrasekhar, García, and Khajehei 2022). This pattern is directly relevant to CBO resilience, where organizations can be deeply embedded in community life while still being weakly positioned in the networks that distribute money, technical assistance, and policy influence.

This literature explains why relationships help CBOs remain present. It says less about whether that support preserves or rebuilds internal capacity. Volunteers, donations, referrals, shared services, and in-kind assistance can sustain service delivery without strengthening reserves, staffing, operating systems, or recovery time. As such, this paper treats relational capacity as a condition-shaping factor rather than as a synonym for resilience. Relational capacity helps explain why CBOs persist, while operational condition shows what persistence is costing them. The analysis in this paper therefore asks which supports and pressures allow some CBOs to preserve or rebuild internal capacity while others draw down staff, reserves, mission scope, infrastructure, or leadership

capacity. It also asks how leaders' broad assessments and survey responses shape what becomes visible or difficult to see about operational condition.

3. Data and Methods

3.1. Sample and Fieldwork Context

This analysis draws primarily on coded interviews with 50 leaders of community-based organizations (CBOs) across 28 states. Organizations were sampled across FEMA disaster-exposure strata, organizational size, service type, and U.S. region (Figure 1). Interviews lasted approximately 45–60 minutes and were conducted between December 2025 and July 2026. The semi-structured protocol covered disruption history, definitions of resilience, planning, finances and reserves, staff well-being, networks, and anticipated organizational threats. Of the 50 organizations, 21 also completed an organizational survey. All condition classifications and comparisons of supports and pressures presented in this paper are based on the interview data alone. Section 4.4 uses one survey item as a limited comparison with the interview findings. All identifying details were removed in this paper, and organizations are referenced only by anonymized study identifiers (IRB #25-10-44).

Sample Demographics

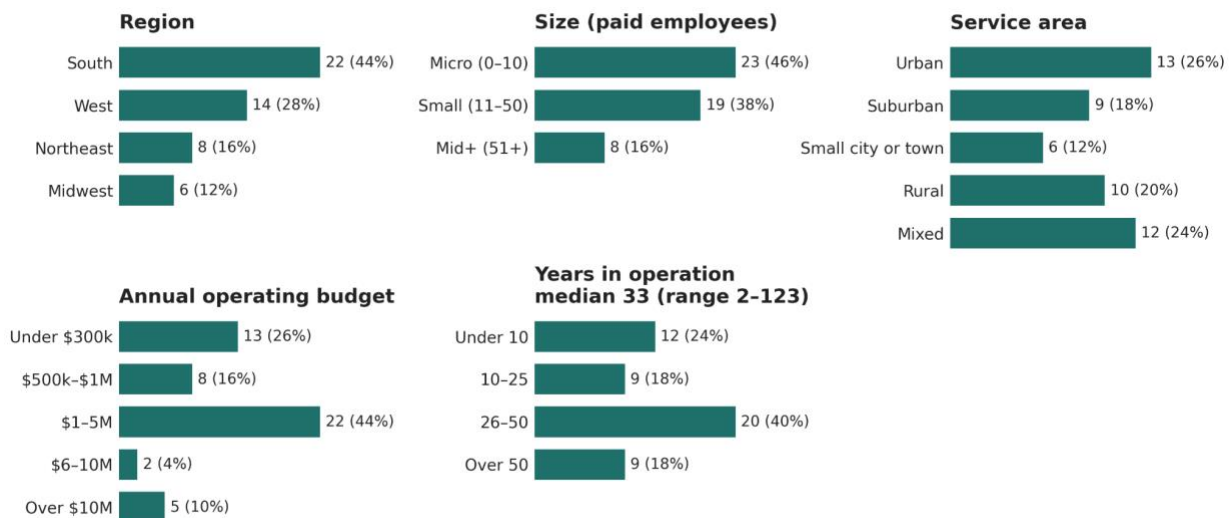


Figure 1. n = 50 CBOs. The under-\$300k budget category includes three grassroots organizations with unreported, fluctuating budgets consistently below that threshold. Years in operation are measured from the tax-exemption year, with several organizations having operated informally or under fiscal sponsorship before incorporating. The percentages may not sum to 100 due to rounding.

The interviews were conducted during a period of unfolding federal funding disruption and political uncertainty, which created a common field-level shock across the sample. Leaders recalled their experiences with current depletion and demand increases in real time, as well as earlier disruptions. This timing makes it possible to compare how organizations across the country persisted amid a shared disruption under different operational conditions. The classifications detailed in the findings are therefore snapshots of organizations under live stress.

3.2. Classifying Operational Condition

I classified each organization's current operational condition using a coding rubric developed and piloted for this study. The first version of the rubric assessed operational condition on a single scale: sustainable, strained, or in depletion. Before applying it to the full

interview set, I piloted this version of the rubric on six transcripts selected for diversity in organizational size, service type, and interview timing. The pilot showed that the single scale was inadequate. Some organizations were financially sound while unsustainably consuming staff or leadership capacity. Others were financially strained but had protected staff capacity. A single scale would have forced a choice between two defensible interpretations and risked determining the study's central outcome variable too early. I therefore separated the rubric into two dimensions, financial condition and capacity condition, and applied both dimensions to all 50 transcripts.

The financial axis described whether revenue and reserves could support current operations. Organizations were coded as financially *sustainable* when revenues roughly covered operations and reserves were intact or improving. They were financially *strained* when budgets were tight but core buffers were not being steadily consumed. Reserve *depletion* applied when reserves or comparable buffers were being steadily spent down without being replenished. The capacity axis described staffing and operational infrastructure. Organizations had *slack* when spare capacity was available and were *lean* when capacity was thin but still functioning. Capacity depletion applied when the organization was steadily consuming staff capacity or infrastructure. This included staff exhaustion linked to persistent resource shortfalls, leaders covering gaps through unpaid labor or personal funds, narrowing of the core mission scope despite continued demand, and infrastructure that the organization could no longer maintain.

I first coded current financial and capacity condition. I then recorded whether strain was temporary or sustained and whether the organization was improving, stable, or worsening. Temporary strain did not count as ongoing depletion unless it became sustained and unreplenished. Surge-and-recover cycles, planned reserve use, and ordinary leanness therefore

did not lower an organization's classification. This distinction matters because leanness was common across the sector, while sustained loss of money, people, infrastructure, or mission scope marked a different condition. Section 3.5 describes the preliminary AI-assisted coding and the manual review used to produce the final classifications. Combining the financial and capacity axes with organizational trajectory yielded four operational conditions. Table 1 defines each condition and reports the number of organizations classified into each.

Table 1. Operational Condition Classifications

Condition	Classification rule	n
Thriving	Financially sustainable with no ongoing capacity depletion	19
Recovering	Current or recent depletion with an improving trajectory	9
Strained Continuity	Financial or capacity strain without sustained, unreplenished loss	9
Depleted Continuity	Sustained reserve or capacity depletion with a stable or worsening trajectory	13

Codes related to organizational trajectory, anticipated exposure, and leaders' overall assessments were kept separate from codes describing current operational condition. This distinction is important because an anticipated funding loss indicates prospective risk and is not evidence of current depletion. Additionally, a leader's broad assessment is subjective and does not replace specific evidence of current depletion. Keeping these codes separate allowed me to

compare them against operational condition. As a separate validity check, I compared the typology with earlier episode-level coding of the same 50 organizations ⁶

3.3. Coding Supports and Pressures

For each organization, I coded the supports and pressures that leaders linked to its current operating condition (Table 2). I then grouped the 816 codes into six categories: financial and material buffers, staffing and overhead, relational support, governance and planning, external pressures, and other vulnerabilities. Table 2 reports the types of supports and pressures organizations faced by factor category (protective vs. depleting), covering the 533 attributions described below.

Table 2. Supports and Pressures by Factor Category

Supports and Pressures	Classification rule	Protective	Depleting
Relational support	Relationships that produced concrete support (money, volunteers, in-kind goods, shared services, or advocacy protection) from community, peers, funders, or partners.	111	1
Financial and material buffers	Reserves, flexible funding, and material resources that cushioned disruption, or their depletion.	85	18

⁶ The earlier analysis coded 326 threat-response episodes as depleted, mixed, neutral, or strengthened. I scored episodes as 1 for depleted, 0.5 for mixed, and 0 for neutral or strengthened, then averaged the scores within each organization. Mean scores rose from 0.51 among thriving organizations to 0.55 among recovering organizations, 0.61 among organizations in strained continuity, and 0.68 among organizations in depleted continuity. Because the two analyses used different units and coding schemes, the increase at each step from thriving to depleted continuity serves only as a limited validity check, not an independent measure.

Staffing and overhead	Staff capacity, benefits and protection, and administrative overhead that absorbed or transmitted strain.	62	10
Governance and planning	Board function, leadership practices, policies, and planning routines that shaped the response.	138	3
External pressures	Conditions outside the organization (the funding environment, policy shifts, and demand changes) bearing on its condition.	26	70
Other vulnerabilities	Remaining depleting factors not captured by the other categories.	NA	9

To avoid circular reasoning, I separated evidence of an organization's condition from factors that might help explain that condition. Some codes that initially appeared to be condition-shaping factors were actually evidence of depletion. For example, unpaid or personally financed leader labor, staff overextension, and deferred infrastructure do not explain depletion, they are forms of depletion. The comparisons of supports and pressures therefore excluded these condition-evidence codes. Of the 831 total coded references, 15 served as condition evidence and 816 as explanatory factors. Each explanatory code was also tagged for evidentiary strength, distinguishing explicit causal support in the transcript from inferred attribution, and for direction. Of the 816 explanatory codes, 706 carried explicit causal support, and 533 of those were coded in a clear direction: 422 protective and 111 actively depleting. Table 2, Appendix Table 1, and Appendix Figure 1 all report that subset of 533. The remaining codes were analyst-inferred (110) or coded as latent vulnerabilities, contingent, or time-varying (173), and are therefore not summarized in the protective-versus-depleting comparison.

3.4. Targeted Coding of Potential Explanations for Operational Condition

After classifying operational condition and coding supports and pressures, three constructs emerged as potential mechanisms that required a second targeted pass of all 50 transcripts. These emergent mechanisms included whether relationships produced concrete support, whether staffing conditions protected staff or contributed to burnout, and whether organizations had time to recover between disruptions.

Relational support included money, volunteers, in-kind goods, shared services, or advocacy protection. The *staffing* check distinguished formal benefits, informal practices such as check-ins and flexible scheduling, structural protection through adequate staffing, pay, and coverage, and current evidence of burnout. *Recovery time* was coded as existing, intermittent or seasonal, not discussed, or absent. I completed these coding rounds without viewing condition labels and joined the results to operational condition.

3.5. AI-Assisted Coding and Manual Verification Process

Each coding phase began with an AI-assisted preliminary pass (Anthropic 2026). During this process I treated model output as candidate codes and not the final analysis. I developed and piloted each rubric, reviewed each transcript in full, verified each candidate code against the source transcripts, revised and removed unsupported codes, and added codes the preliminary passes missed. All AI-assisted work followed the study's data-protection protocol (IRB #25-10-44) and Northeastern's AI Review Committee guidelines, which permit AI-assisted analysis of de-identified data through university-approved tools and prohibit entering identifiable participant data. The de-identified transcripts were maintained in a password-protected folder in my

Northeastern University OneDrive account and accessed from my password-protected laptop, and organizations were referenced only by anonymized study identifiers. Each code used in the analysis was linked to supporting de-identified transcript evidence in a table format.

3.6. Analytic Approach and Scope

The analysis includes 50 organizations across four operational conditions, so I treat percentages as descriptive patterns, not population estimates. I report bases for each comparison and treat the factor analyses as associational descriptions of the coded corpus, not as hypothesis tests. For the 21 organizations that completed both instruments, I compared the interview-based condition coding with the survey item asking how disruptions affected eight organizational capacities. Responses ranged from -2, significantly depleted, to +2, significantly strengthened.

Section 4.4 reports this limited comparison.

4. Findings

When asked what resilience meant for their organizations, leaders rarely began with the language of risk assessment, continuity planning, or formal preparedness. They described resilience as an everyday practice—enduring, staying present, continuing to serve, maintaining relationships, and remaining faithful to the mission:

Scarcity can be the drumbeat, and doing more with less year after year after year is kind of how we grind it out. (Northeast, philanthropic intermediary)

I think you just have to have the commitment, you know, it requires a passion and commitment that's not required in the private sector when you work for a big company. (Midwest, food pantry)

We have done this work with some money, with a lot of money, and with no money at all, we have always done the work. We have always found a way to get the work done... (South, environmental justice organization)

You just got to show up. You just got to keep moving forward. You just have to do the next right thing. And you have to always be willing to pivot and change based on surveying the landscape. You know, just always willing to change. (South, human services organization)

Two features of this conceptual landscape matter for the operational condition analysis. First, resilience as endurance does not specify what endurance costs. An organization that endures by spending down reserves or exhausting a leader can satisfy an endurance definition as easily as one that endures from a more stable position. Second, leaders' definitions often had a collective and moral tone. They focused on whether the organization remained present for the community, whether the work continued, and whether relationships were maintained. These are essential dimensions of CBO resilience, but they do not fully capture the organization's internal operating condition. The condition analysis therefore compared broad mission-based assessments with specific evidence about finances, staffing, operations, and recovery time. Section 4.4 returns to the difference between these two assessments.

4.1. Four Operational Conditions

Every organization in this sample was operating and serving its community at the time of the interview. When coded on the financial and capacity axes, this persistence separated into four conditions: 19 thriving, 9 recovering, 9 in strained continuity, and 13 in depleted continuity.

First, thriving usually meant lean operations without ongoing depletion (Figure 2). Eighty-nine percent (17 of 19) of thriving organizations were coded as lean. In this sector, thriving does not necessarily require abundant slack. It meant that finances, staffing, and routines

could absorb pressure without steadily consuming reserves, staff capacity, infrastructure, or mission scope.



Figure 2. The financial × capacity grid shows one dot per organization (n = 50), colored by condition. Recovering and depleted organizations often occupy the same cell: the grid shows current position, and recovering organizations have not yet rebuilt the reserves or capacity they lost. What distinguishes them is direction (improving versus stable or worsening) coded separately from position.

Second, most depletion occurred through capacity, not finances. Only 23 percent (3 of 13) of organizations in depleted continuity were experiencing financial depletion. The other 10 were consuming people, mission scope, or infrastructure while their finances were strained or stable. Two of those organizations were financially sustainable while still depleting their capacity. In 69 percent (9 of 13) of cases, leaders filled organizational gaps by working without pay, spending their own money, or taking on work at a cost to their health. These costs rarely appear on financial statements. Financial monitoring alone would therefore miss most cases of depleted continuity. One leader described absorbing the sudden arrival of migrants without a funded program to meet the need:

We had more than 50 individual young men and women ... sitting down from 8 a.m., the moment I open the door, to 5 p.m., and they have no place to go. ... We buy them breakfast, we buy them lunch. Sometimes we can't afford it, [so] I'll just cook at home. I'll cook big pans of pasta or big bowls of rice in the morning and bring it with me. (Northeast, refugee services organization)

Third, operational condition and organizational trajectory are different (Figure 3). Recovering and depleted organizations often occupied the same cell because both have experienced sustained loss. Trajectory distinguished them. Recovering organizations were *improving* through new leadership practices, funding, reserves, or other changes. Organizations in depleted continuity were *stable* or *worsening*. Growth also did not necessarily signal health when demand increased faster than resources could be replenished. Treating resilience as a static attribute would miss these directional differences.

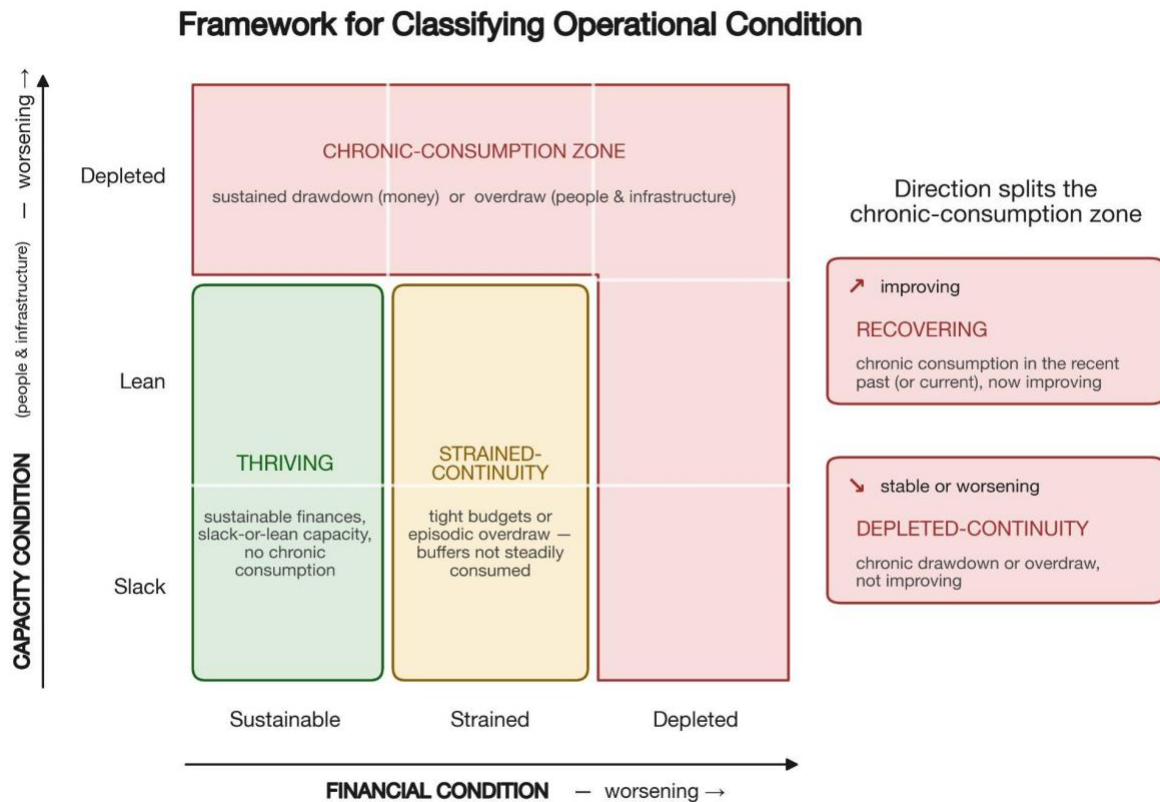


Figure 3. Operational condition was classified from financial condition and capacity condition. Sustained, unreplenished loss on either axis placed an organization in the chronic-consumption zone. Trajectory then separated recovering organizations from those in depleted continuity. Organizations without ongoing depletion were classified as thriving or strained continuity. Temporary strain, planned reserve use, and ordinary leanness did not count as depletion unless they became sustained and unreplenished.

4.2. Relational Support Sustains Persistence Across Conditions

Relationships helped organizations in every condition remain open. Leaders in the study consistently credited community relationships, peer networks, funders, volunteers, and partners as central to continued operation (Appendix Table 2). However, in another sense, the data complicate the relational account. Relational capacity did not distinguish thriving organizations

from depleted ones. Community embeddedness was coded as protective for 84 percent of thriving organizations and 62 percent of organizations in depleted continuity. Per organization, depleted-continuity cases had nearly as many protective relational attributions as thriving cases (Appendix Table 1). The organizations being depleted were not abandoned by their communities.

The recoding process described in Section 3.4 tested whether relationships were protective only when organizations could convert them into usable support. Usable support included money, volunteers, in-kind donations, shared services, and advocacy protection. This conversion of relationships to support appeared in both thriving and depleted organizations. The presence of usable support therefore did not explain the difference between the two conditions.

I therefore interpret relational support as a core component of operational persistence. It helps explain why these organizations remain open, but it does not explain which organizations thrive versus become depleted. The difference is not simply whether support exists or whether it converts into tangible help. The difference is whether converted support can accumulate into buffers, staffing, routines, and recovery time, or whether it is consumed immediately by demand.⁷

4.3. Internal Capacity and Recovery Distinguish Thriving from Depleted Continuity

Four patterns distinguished thriving organizations from those in depleted continuity: financial and operational buffers; whether threats remained future risks or became current pressures; adequate staffing, pay, and coverage; and time to recover. Financial and operational buffers showed the largest differences. COVID-era reserves were coded as protective for 58

⁷ Appendix Figure 1 presents the full comparison of protective and depleting references across categories and operational conditions.

percent of thriving organizations and 8 percent of organizations in depleted continuity. Other supports followed the same pattern: scenario planning (74% versus 38%), staff and overhead investment (58% versus 23%), engaged boards (42% versus 23%), and diversified funding (47% versus 23%). These are ordinary organizational supports, including reserves, unrestricted dollars, planning time, staff coverage, and administrative infrastructure. A leader of a thriving organization described how pandemic-era funds became standing capacity:

The pandemic and people's understanding of the nature of hunger and food insecurity has led to resources that have enabled us to put that back into creating resilience within our system. (South, food bank)

By contrast, leaders in depleted continuity described funds that never translated to durable capacity or had already been consumed, exposing the limits of their financial cushion:

COVID ... created an artificial bubble where now a lot of organizations are facing the reality of what happens when those grants are cut. (South, immigrant and refugee services organization)

If you would have asked me before everything that happened at the beginning of 2025, I thought our cushion was much more bouncy than it was. ... This month was the first month I had to cash out a CD. And it was really depressing, because we had been able to make it work up until that point, no matter how difficult it was, and there was just no way... We had a food bill that was higher than one we've seen before. ... There's no way to say, well, we'll put this on hold for another month. It just doesn't work like that. (South, human services organization)

Similar threats did not have the same effect in every organization. Of the 50 organizations, 43 described direct or anticipated federal funding losses in 2025–2026. . In thriving organizations, these pressures were more often future risks that leaders monitored or planned around. In depleted organizations, similar pressures were already consuming resources. Actively depleting external-pressure and demand references rose from 0.3 per thriving organization to 2.5 per organization in depleted continuity. Federal funding dependence was coded 9 times as a future risk and zero times as an active pressure among thriving organizations.

It was coded 7 times as an active pressure among depleted organizations. Threats became depletion when organizations lacked buffers and room to respond.

Staffing conditions also separated thriving from depleted continuity. Informal care practices, including check-ins, debriefs, and flexibility, appeared across conditions and did not distinguish the two groups. Formal supports also showed no clear pattern. The difference was whether leaders described adequate staffing, pay, and coverage as protecting staff or understaffing as the source of burnout. Informal care cannot offset a persistent shortage of people. When staffing is inadequate, informal care practices become load-bearing and eventually fail. The following quotes from organizational leaders illustrate these narratives:

Understaffing as a source of burnout: I think that when you have such a small staff, if you have a rollover in one staff person, that's 25 percent of your staff, I'm having a rollover in two, which is 50 percent of my staff, and that affects everything that happens. (Northeast, community foundation)

Staffing as structural protection: We also have a retention bonus structure, so if [employees] stay with us, 30-60-90 days, they get 120 days, they get bonuses each increment up to \$1,000 and then we also implemented a plan where it's called the longevity bonus, where, if you're here three, 6 or 10 years, you get \$1 more an hour. And so we implemented it last year. And so we even gave the people who have been with us, like 13 or 14 years. We gave them \$3 more an hour, which is huge. (South, housing organization)

Recovery time was the sharpest discriminator (Figure 4). Seventy-four percent of thriving organizations described real breathing room between disruptions or deliberate practices that created it. In contrast, 77 percent of organizations in depleted continuity and 89 percent of organizations in strained continuity described permanent catch-up. They moved from one disruption to the next without fully recovering. Planning was deferred, staff remained in response mode, and leaders never fully left crisis conditions. Only 11 percent (2 of 19) of thriving organizations were coded as permanent catch-up. Recovery time is where the other mechanisms

converge. Buffers buy time, staffing creates the capacity to use it, and unbuffered exposure consumes it.

No recovery time: We never really left disaster mode after COVID... after COVID, there was high, high inflation, which caused a kind of economic disaster for the people that we served. And so we really kind of just kept going at high level. (South, human services organization)

There's a lot of urgency in what we do — reactivity. And I think that's inherently really stressful. ... During the government shutdown, we were also hiring, we were also doing all these other things at the end of the year ... with no way to pause. And so we kind of put our heads down and get through it, which is not necessarily healthy, but I don't see another way around it. And so I think sometimes we don't know how to do better, because we have to survive. (Northeast, food-security advocacy organization)

Time to Recover: But we came out of it actually stronger, and we learned a lot. (South, housing organization)

Together, these patterns characterize depleted continuity. These organizations are often rich in relationships but they face cumulative pressures without enough buffers, staff capacity, or recovery time. Community support is converted directly into service delivery, but it does not accumulate as durable capacity. The remaining gap is absorbed by people, often by one leader. Depleted continuity is what mission-driven organizations look like when relational support, commitment to the mission, and leader labor are asked to compensate for structural shortfall.

Recovery Windows and Staffing Protection by Operational Condition

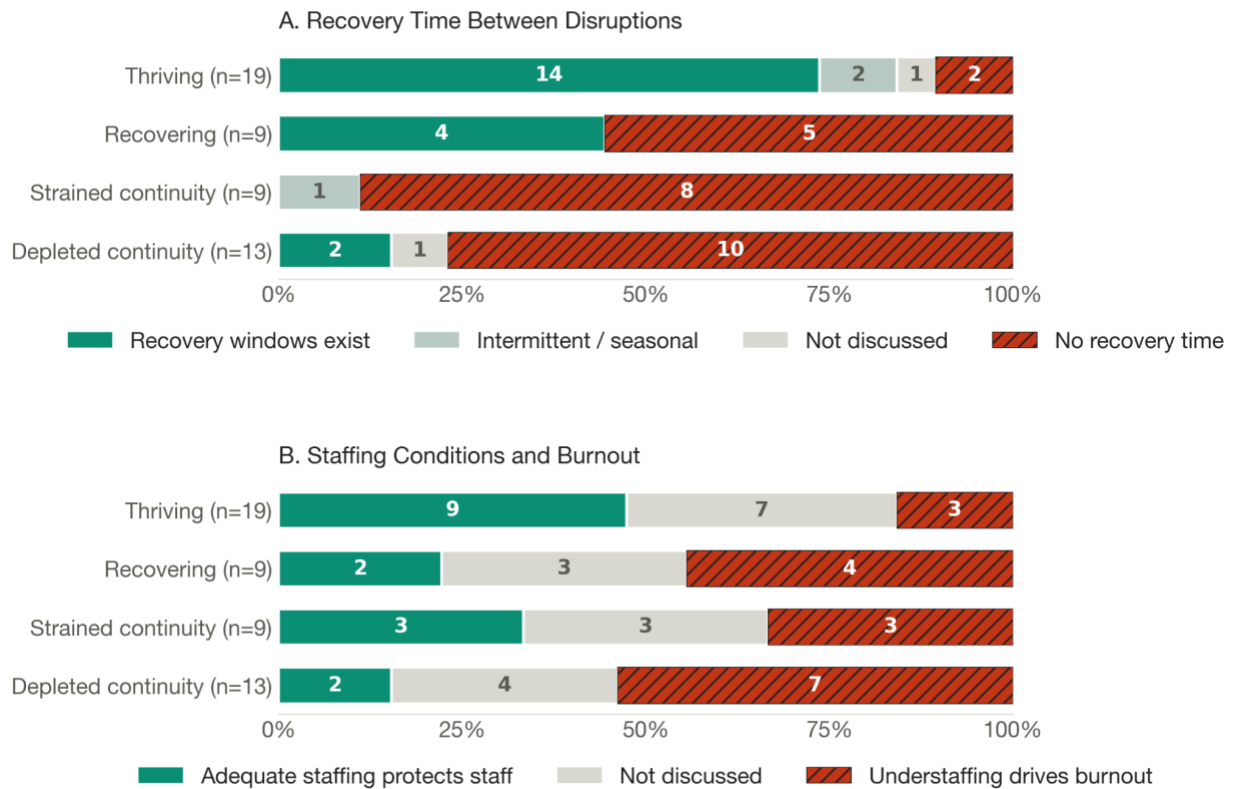


Figure 4. Panel A shows whether organizations had recovery windows between disruptions, intermittent or seasonal recovery, or no recovery time between disruptions. Panel B shows whether leaders described adequate staffing, pay, and coverage as protecting staff well-being, or understaffing as driving burnout. Counts are organizations from the targeted re-code of all 50 interviews; bar lengths are within-condition shares.

4.4. Leader Self-Assessments Can Obscure Operational Depletion

The final analysis compared leaders' broad assessments with specific evidence about operations. I coded whether leaders described the organization as thriving, managing, or struggling; their outlook as confident, vigilant, or threatened; and whether that assessment aligned with or diverged from the interview-based condition classification.

I found that all 19 leaders of thriving organizations gave assessments consistent with their operational condition. Most remained vigilant. Their accounts recognized risk while describing a

predominantly stable or improving position. Among organizations in depleted continuity, 11 of 13 leader assessments diverged at least partly from the condition coding. Only 2 leaders described their organizations as struggling. Another 9 described them as managing, and 2 described them as thriving. This difference did not reflect denial. Leaders described the costs of persistence in detail, including exhaustion, deferred work, personal subsidy, and uncertainty. However, they evaluated the organization through a different standard: whether the mission continued, whether the community trusted them, and whether they were still showing up. By that standard, many were succeeding:

We're nonprofits, so we're not ever looking at, oh, what's our bottom line? I mean, we watched that because we didn't want to bounce checks, but the biggest thing for us is, what are we doing for our clients, and how can we do better? (South, human services organization)

Funders, boards, and researchers often learn about organizational condition through grant reports, site visits, needs assessments, surveys, and interviews. Broad assessments of mission continuity can obscure internal depletion. This is especially likely when costs take the form of unpaid leader labor, health, time, and deferred work, none of which is immediately visible. Depleted organizations also retain visible signs of strength, including active services, community support, volunteers, and committed leadership. One participant, who works on the funding side, described this visibility problem clearly:

Nonprofits out here are a lot like ducks on a pond. On the top they just look like they're gliding along, but then underneath they're paddling like crazy. So sometimes they're going to tell you why they're paddling like crazy, and other times, because you're a funder, they're not. But eventually you find out. (Northeast, community philanthropic intermediary)

Of the 21 organizations that completed both instruments, 20 answered the survey item asking how disruptions affected eight capacities. The scale ranged from -2, significantly depleted, to +2, significantly strengthened. The 3 organizations in depleted continuity reported

an average gain of +0.62, similar to +0.57 among the 11 thriving organizations with survey data. These small cells do not establish a group difference. Their direction matches the interview finding. Broad self-report items captured adaptation and continued service more readily than internal depletion.

The issue is not deception. Leaders and the condition coding answer different questions. Broad assessments ask whether the mission continued. The condition coding asks what the organization consumed to maintain that continuity.

5. Discussion and Implications

This paper shifts the study of organizational resilience from *whether organizations persist to the condition in which they persist*. Continued operation should not be treated as evidence of organizational health. The organizations in this study often had adaptive capacity, enacted effective response processes, and remained open through disruption. Yet some did so while drawing down staff capacity, reserves, infrastructure, mission scope, or leadership capacity. Operational condition makes those costs visible and shows what state an organization carries into the next disruption.

Relational support explains persistence more clearly than operational health. Relationships kept CBOs open across all four conditions. They protected condition when concrete support preserved reserves, staffing, systems, or recovery time. They sustained service without restoring condition when immediate demand consumed the support as quickly as it arrived.

Recovery time should also be treated as part of organizational condition. An organization cannot replenish resources when disruptions arrive faster than recovery can take place. In this

study, time to recover was the clearest difference between thriving and depleted continuity. Resilience measures should therefore ask what organizations have, what they do, and whether they have time to replace what disruption consumes.

For organizational sociology, depleted continuity identifies an organizational condition that closure-based research cannot see. These organizations remain open and do not fully recover. Community support, mission commitment, and unpaid or personally financed leader labor hold them together. Much of the cost remains invisible because leaders, staff, and deferred infrastructure absorb it before financial statements show failure.

For researchers, the implications are methodological. Distinguishing operational condition helps specify what kind of resilience an organization has and what support might move it from depleted continuity toward sustainable operation. For funders and intermediaries, the implications are practical. CBOs often have strong incentives to present stable, effective operations to funders even when internal capacity is strained. Funders should ask whether reserves are stable or declining. They should ask whether staffing matches demand, when the organization last had time to recover, whether leaders are subsidizing operations, and what work is being deferred. The supports that distinguish thriving from depleted continuity are ordinary and fundable: unrestricted dollars, reserves, staff coverage, planning time, and protected recovery time after disruption. The recovering category also shows that depletion can change when funding, staffing, leadership practices, or funder flexibility improve. As one leader put it:

Nonprofits are in a great position to affect community change and to build resilience for local communities — they just need the resources to align. (West, human services organization)

6. Limitations

Four limitations bound the claims made in this study. First, the sample includes organizations that were still operating at the time of interview and does not include organizations that had closed or chose not to participate. Second, operational condition was coded from single interviews conducted during an unusually turbulent period. The classifications are snapshots, and organizations can move between conditions. Third, Claude supported the preliminary coding and all final coding decisions were made by the author. Each retained code was linked to supporting transcript evidence. The focused recoding was completed without viewing condition labels. These safeguards strengthen consistency without replacing independent coding. The survey comparison in Section 4.4 also rests on a small subsample. The relevant item was answered by 20 organizations, including 3 classified as depleted continuity. Fourth, the sample size limits the interpretation of patterns in supports and pressures. I treat percentages as descriptive, not as estimates of population effects. The inclusive definition of concrete relational support also requires further testing with independent coding and network data.

7. Conclusion

All 50 organizations in this study were open. That fact did not mean they were in the same condition. Their conditions differed: 19 were thriving, 9 were recovering, 9 were in strained continuity, and 13 were in depleted continuity. Some continued from a stable position. Some were rebuilding. Some were getting by under pressure. Others remained open by consuming reserves, infrastructure, mission scope, staff capacity, or leader health.

Continued operation alone cannot distinguish these conditions. Operational condition can. Community support, commitment, and adaptive skill appeared across all four groups. The difference was whether those strengths were paired with buffers, staffing, organizational routines, and time to recover. In depleted continuity, persistence often depended on the resource

mission-driven organizations are most likely to hold in reserve: a person who will not quit. One food-pantry director reflected:

When an organization is volunteer run, and one volunteer goes, ‘Yeah, I don’t want to do this anymore,’ and they walk out — everybody goes into a panic. ... In fact, I had a gentleman visit yesterday. In his community, the local pantry is going to stop because [the director] doesn’t want to do it anymore, and so she’s just going to close it. (Midwest, food pantry)

Remaining open does not answer the question of organizational resilience. It is the starting point for asking what condition the organization is in, what is it consuming to keep serving, and can those resources be replenished?

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Appendix: Supplemental Tables

Table 1. Factor Attributions by Analytic Family, Direction, and Operational Condition

Analytic family	Direction	Thriving (n=19)	Recovering (n=9)	Strained continuity (n=9)	Depleted continuity (n=13)
Relational support	Protective	47	23	15	26
Relational support	Depleting	0	1	0	0
Financial and material buffers	Protective	47	15	8	15
Financial and material buffers	Depleting	1	1	4	12
Staffing and overhead	Protective	25	10	12	15
Staffing and overhead	Depleting	3	2	0	5
Governance and planning	Protective	62	29	20	27
Governance and planning	Depleting	1	0	0	2
External pressures	Protective	10	7	5	4
External pressures	Depleting	5	14	18	33
Other vulnerabilities	Protective	0	0	0	0
Other vulnerabilities	Depleting	1	1	3	4

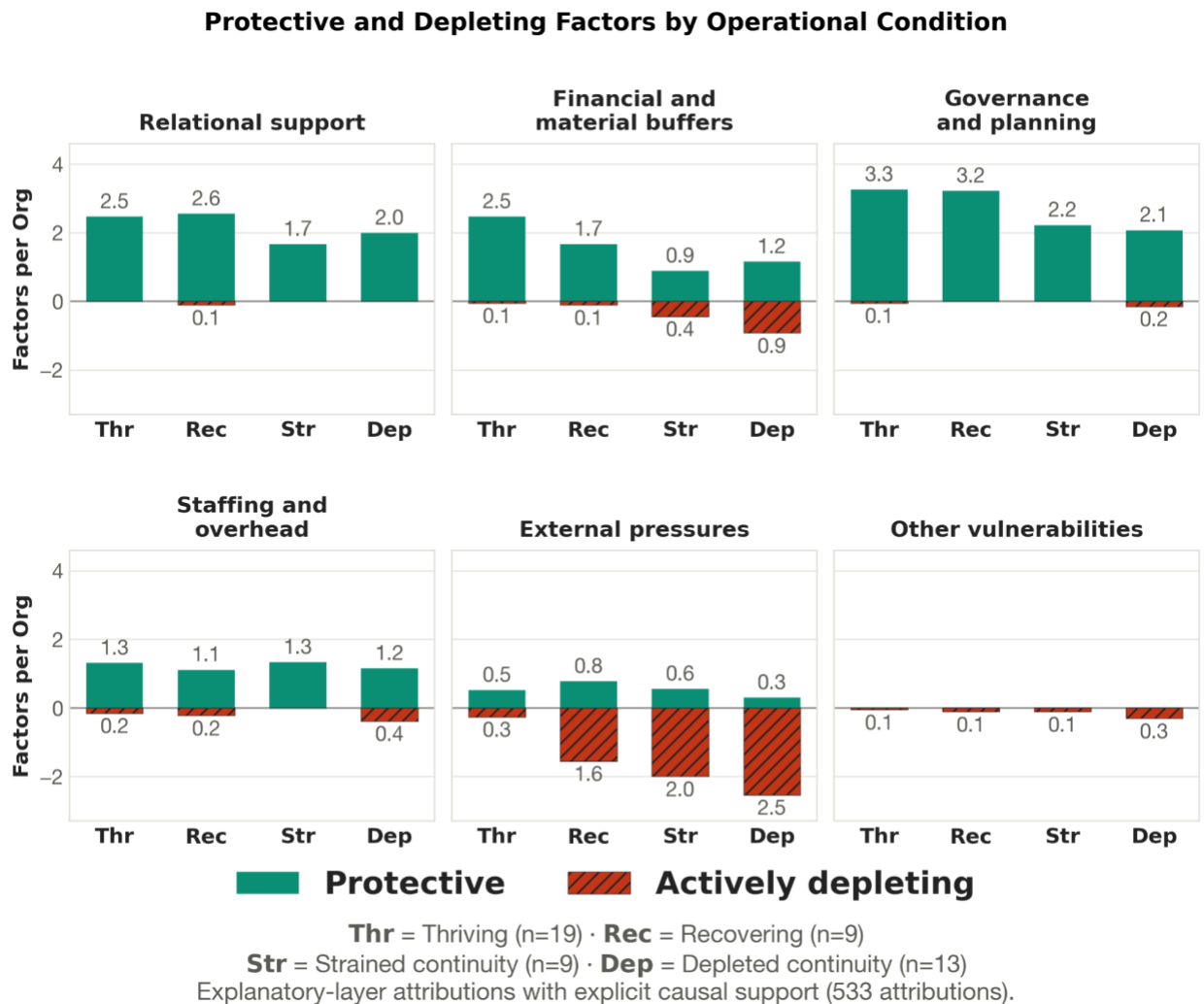
Note. Cells count explanatory-layer attributions coded protective or depleting with explicit causal support in the transcripts. The zeros are informative, indicating relational infrastructure was almost never coded as a depleting pressure in any condition, and other vulnerabilities are depleting by definition.

Table 2. Illustrative Evidence for Condition-Shaping Factors

Analytic family	Direction	Illustrative quote	Condition; region, organization type
Relational Support	Protective	“The church was able to step in and do that because we didn’t have the funds.”	Depleted continuity; South, human services organization
Financial and material buffers	Protective	“COVID brought in a lot of extra funds that we used very wisely.”	Thriving; Midwest, food-assistance organization
Staffing and overhead	Protective	“When you pour into your people, your people are going to give back to you.”	Recovering; South, human services organization
Staffing and overhead	Depleting	“I tried to hire a development person, and I didn’t really get anybody... we didn’t get any decent candidates because of the salary we were able to offer, and we have no benefits.”	Depleted continuity; Midwest, food-assistance organization
Governance and planning	Protective	“Planning is very important to us... we have a very robust set of policies and procedures.”	Strained continuity; Northeast, community-improvement organization
Governance and planning	Depleting	“Once their job doesn’t dictate that they come to our meetings... they don’t... someone might come with great ideas, and then we never see them again.”	Depleted continuity; Midwest, advocacy coalition

External pressures	Protective	“We try to be as apolitical as possible, because we... have supporters from all walks of life.”	Thriving; West, human services organization
External pressures	Depleting	“Scarcity can be the drumbeat, and doing more with less year after year after year is kind of how we grind it out.”	Strained continuity; Northeast, philanthropic intermediary
Other vulnerabilities	Depleting	“I can handle a lot of sacrifices that not everybody else can. So I tend to wind up being there the most frequently.”	Depleted continuity; West, community center
Other vulnerabilities	Depleting	“A lot of the work that I’m doing is coming out of my pocket, because I don’t have any funding for that, because I don’t know who to ask, so this is a lot.”	Strained continuity; South, micro environmental- justice organization

Figure 1. Protective and Depleting Factors by Operational Condition



Note. Shows the mean number of condition-shaping factor attributions per organization, by analytic family and operational condition. The bars above zero show attributions coded as protective; bars below zero show attributions coded as actively depleting. Protective relational support attributions are similar across the four conditions, whereas actively depleting external pressure attributions increase from 0.3 per organization among thriving organizations to 2.5 among organizations in depleted continuity. Full attribution counts by family, direction, and condition appear in Appendix Table 1, which reports the same causal-support subset.

CONCLUSION

“Healthy communities have healthy institutions in them”
(South, community development organization)

Together, the three papers show that organizational resilience in community-based organizations (CBOs) cannot be understood through disaster exposure, continued operation, or financial stability alone. At the county level, recurrent FEMA-declared disaster exposure is not associated with meaningful average change in social capital over the periods observed. At the organizational level, differentiated threat environments shape the capacities CBOs build, activate, or deplete and reveal where internal capacity-building reaches its limits. Within organizations, leader accounts show that continued operation can coexist with substantial depletion. The dissertation therefore shifts attention beyond whether communities and organizations endure disruption. It asks how endurance is organized and resourced, which capacities are built, and what is strained or depleted in the process.

1. Summary of Findings

Paper 1 finds that recurrent FEMA-declared disaster exposure does not meaningfully change county-level bonding, bridging, linking, or composite social capital. The cross-sectional disadvantage of disaster-prone counties disappears when baseline-similar counties are compared, indicating that aggregate social capital is relatively stable at this scale. Paper 2 shows where disruption registers more clearly. CBOs face differentiated, recurring, and sometimes overlapping threat environments that extend beyond natural hazards to financial, staffing, demand, health, technical, political and regulatory, and less frequently, violence and safety pressures. Threats that deplete a specific resource often call forth investment in that same resource, while health and demand shocks are absorbed largely through operational change.

Social capacity (the ability of organizations to draw on partners, coalitions, volunteers, funders, community backing, and internal trust) appears across threat types as standing infrastructure, and political threats mark the limit of internal capacity-building. Paper 3 shows why continued operation is an incomplete measure of the resilience of an organization or the success of a sector. Relational support and mission commitment were widespread across organizations in very different operational conditions. More sustainable organizations paired those strengths with financial buffers, staff and operational investment, institutionalized routines, and time to recover. In depleted continuity organizations, survival often depended on leaders and staff absorbing additional work, using personal resources, or allowing infrastructure to erode.

2. Contributions and Implications

I think it's a great topic, especially nowadays, as we experience a shift in the priorities from the federal administration with regards to social services in general. So, thank you for picking this important subject. (South, senior services)

The papers in this dissertation shift resilience away from a trait or score and toward a threat-informed account of capacity investment and operational condition. Community resilience is often discussed as if community-level strength automatically carries over to organizational strength. Stable county-level social capital can coexist with substantial strain among the organizations that sustain community ties and services. This is not a causal claim that organizational depletion produces aggregate stability. It is a warning that the aggregate durability of social capital at the county level can obscure where the costs of disruption are carried.

The implications for funders, public agencies, and nonprofit boards are direct. If CBOs are expected to anchor community resilience, then resilience support cannot be limited to short-term program grants, narrow deliverables, or emergency response only after a visible shock. Organizations need greater support in the areas that make persistence replenishable: unrestricted

funding, staffing investment, administrative infrastructure, updated technological systems, planning time, and reserves. These resources need to be seen as part of how mission work survives. Evaluating success based on an organization's ability to maintain its regular delivery of services or keep operational costs low is insufficient. Funders and boards should ask better questions. They should ask what work is being deferred, what support is being consumed as quickly as it arrives, which people are carrying work beyond sustainable limits, and what resources would allow the organization to recover before the next disruption. Operational continuity can disguise the true costs of keeping an organization afloat. Additionally, CBOs often have reasons to present strength. They need to maintain community trust, reassure funders, protect staff morale, and keep services moving. Funding that rewards visible continuity while underfunding staffing, overhead, and planning may preserve short-term services while weakening long-term capacity.

For CBOs, this dissertation offers language for naming pressures that are often felt but hard to communicate in grant reports or strategic plans. It makes it easier to say that a relationship helped but did not solve the staffing problem; that a successful emergency pivot still depleted staff; that a technology tool may save time only if the organization has the skill and governance to use it safely; or that planning cannot become real when every hour is absorbed by immediate demand. This language matters because what cannot be named is difficult to fund, measure, or protect.

3. Future Research

This dissertation introduces several priorities for future research. First, researchers should study organizational condition over time. A longitudinal design could show how organizations move between conditions and what support prevents depleted continuity from ending in closure.

A broader design could also use administrative records to bring closed organizations and nonparticipants into view. This would clarify whether the patterns identified here extend beyond surviving CBOs.

Second, stronger measures of organizational condition are also needed. Financial ratios, closure, and service continuity each capture only part of organizational health. Measures should assess staff capacity and leadership burden. They should also capture deferred infrastructure, reserve use, recovery time, and mission narrowing. Researchers could test these measures through surveys, administrative records, interviews, board documents, and repeated organizational check-ins.

Third, the OR-TIIF should next be connected to organizational outcomes. The framework identifies what organizations build, activate, or draw down under different pressures. It does not establish which investment profiles preserve capacity over time. Studies could test whether standing capacity reduces depletion. They could also identify which threats exceed the reach of organizational adaptation and whether funder flexibility changes the relationship between disruption and operational condition.

The funding and policy systems in which CBO resilience is built also need closer study. Many leaders in this project described a gap between what funders support and what organizations need in order to remain healthy. Funding structures can stabilize organizations or intensify volatility. Research should examine the effects of restricted grants, reimbursement delays, overhead limits, short funding cycles, reporting demands, and shifting public priorities. These are questions of power as well as management because CBOs depend on systems they do not control.

Technology and AI adoption present another capacity question. Organizations in this study varied widely in their readiness to incorporate new tools. Some were cautious and others felt they were already far behind the curve. Research should examine which CBOs can adopt AI and other digital systems safely and how they use them. It should also test whether adoption narrows or widens capacity gaps. These technologies raise questions about confidentiality, staff skill, governance, cost, community trust, and the distribution of benefits when work is reorganized around new systems.

The findings should also be tested across different organization types. Larger nonprofits, mutual-aid groups, public agencies, and for-profit firms operate under different pressures and absorb disruption through different structures. Comparative research could identify what is specific to small and medium-sized CBOs. It could also show what applies more broadly to organizations working under repeated disruption.

4. Sustaining CBO Resilience

The practical stakes of this dissertation project are straightforward. Healthy communities cannot depend indefinitely on organizations whose internal capacities are being depleted at a rate they cannot sustain. CBOs can keep showing up for a long time, and many do, on stretched budgets and limited paid staff. That persistence is real and should be recognized. But recognition is not enough.

This point is becoming more urgent as access to public benefits becomes increasingly restricted in the United States. A recent New York Times report from Arizona described how more paperwork and new error-penalty incentives in the Supplemental Nutrition Assistance Program (SNAP) have pushed eligible households off food assistance and have driven more people toward food banks and other charities (DeParle 2026). For CBOs, policy shifts like this

are not an external backdrop; they change the threat environment in which they operate by increasing demand for their services. The findings in this dissertation suggest that the nonprofit system cannot absorb such pressure indefinitely through mission commitment and community ties alone. When safety-net access becomes harder, sustaining CBO resilience requires investing in the financial, staffing, operational, technological, and relational capacities that allow organizations to respond without consuming themselves.

A stronger resilience agenda must ask what would allow CBOs to remain present without depleting the people, reserves, infrastructure, and trust that make their work possible. Better disaster plans address only one part of the problem. CBOs also need stable funding, adequate staffing, durable systems, planning time, and room to rebuild between disruptions. These everyday conditions make recovery possible. Sustaining CBO resilience means sustaining the organizations themselves. As one interviewee stated: “Healthy communities have healthy institutions in them” (South, community development organization).

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