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Qiannan Shen
Boston University https://orcid.org/0009-0007-9492-1773
Dingyuan Liu
Dingyuan_Liu@kenan-flagler.unc.edu
University of North Carolina at Chapel Hill https://orcid.org/0009-0009-3665-9310
Yue Zou
Columbia University https://orcid.org/0009-0007-2713-637X
Zhiying Xiao
Worcester Polytechnic Institute
Tongchen Zhang
Independent Research https://orcid.org/0009-0003-9076-0678

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Article

Business Resilience Index (BRI): Evaluating Economic Recovery through Event-Study Heterogeneity

Qiannan Shen [1,†], Dingyuan Liu [2,†,*], Yue Zou [3], Zhiying Xiao [4], Tongchen Zhang [5]

[1] Graduate School of Art and Science, Boston University, Boston, MA, USA; iamqb@bu.edu
[2] University of North Carolina at Chapel Hill, Chapel Hill, NC, USA; Dingyuan_Liu@kenan-flagler.unc.edu
[3] Fu Foundation School of Engineering and Applied Science, Columbia University, New York, NY, USA; yz4200@columbia.edu
[4] Department of Civil, Environmental, and Architectural Engineering, Worcester Polytechnic Institute, Worcester, MA, USA; hebeying0711@gmail.com
[5] Independent Research; tzhangaca@gmail.com
* Correspondence: Dingyuan_Liu@kenan-flagler.unc.edu
† These authors contributed equally to this work.

Abstract

This paper develops a Business Resilience Index (BRI) that measures county-level resilience to natural disasters at a county quarter frequency for the United States over 2014-2024. The index integrates high-frequency labor-market outcomes from the Quarterly Census of Employment and Wages with flood insurance policy information from FEMA, disaster damages from the NOAA Storm Events Database, and social and health determinants from County Health Rankings. Starting from a broad candidate set, we apply an interpretable feature-screening pipeline to retain 79 variables and then use principal component analysis to extract four orthogonal structural dimensions of resilience: Market Scale, Resilience Capacity, Safety and Risk Profile, and Workforce Dynamics. We construct a domain-weighted Strategic Index and benchmark it against data-driven and equal-weight alternatives, showing that county rankings are highly stable across weighting schemes. To evaluate whether the BRI aligns with recovery behavior under acute shocks, we implement a matched difference-in-differences event study around two major flood episodes, Texas 2015Q2 and North Carolina 2018Q3. Conditional on exposure intensity and matched comparability, higher pre-event BRI counties exhibit earlier stabilization and a stronger post-event employment path relative to lower BRI counties, with differences in magnitude and timing across cases. Overall, the BRI provides an interpretable, high-frequency baseline for identifying capacity constraints that may slow recovery and for supporting preparedness targeting and post-disaster monitoring.

Keywords: Business Resilience; Natural Disasters; Labor Market; Principal Component Analysis; Flood Insurance; Event Study

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1. Introduction

In an age of growing climate and economic uncertainty, the ability of local business ecosystems to adapt to and withstand shocks is an emergent area of research. Yet metrics of economic performance that are typically used—quantities like GDP and unemployment rates[1]—tell only half the story. Resilience is far more nuanced than simple indicators like GDP or unemployment rates. A region's ability to recover from a flood or financial downturn[2] depends on many interrelated factors, from the characteristics of the labor

market to the physical sustainability of the location, financial security through insurance, and the general well-being of the workforce.

Much literature already exists on community resilience.[3,4] Yet many of the existing resilience indices developed in the literature have serious gaps[5]—especially in terms of measurement and time resolution. Most resilience indices calculate their metrics on an annual basis without regard for intra-year fluctuations in recovery processes that can occur after disasters strike.

This paper closes this gap in the literature by creating a novel Business Resilience Index (BRI) that is determined not only on a county-by-county basis but also with a time resolution of a quarter rather than annually[6]. This index incorporates high-frequency labor market data drawn from the Quarterly Census of Employment and Wages (QCEW), local-scale flood risk data, and policies governing flood insurance from the Federal Emergency Management Agency (FEMA), as well as social determinants of health from the County Health Rankings project[7], and record information of past disasters from the National Oceanic and Atmospheric Administration (NOAA).

This work contributes to the literature in two important ways. The first contribution is to identify a set of characteristics among nearly 80 features of this dataset that can be reduced by means of a sophisticated feature selection routine coupled with a Principal Component Analysis (PCA) algorithm to four orthogonal features[8,9] that are each meaningful[10] in and of themselves: Market Scale, Resilience Capacity, Safety/Risk Profile, and Workforce Dynamics[11]. The second contribution is to demonstrate that while the structure of the data imposes a weighting scheme on each feature[12] that favors Market Scale above all else, the resilience signals that underlie the metrics remain robustly evident in each of the different configurations[13,14] of the indices that can be specified in a given resilience modeling environment.

By moving from an annual to a quarterly panel structure[15], the resulting index is far more reactive[16] in its appearance than earlier forms of the same index. Rather than informing policymakers or insurance industry analysts for upcoming years in advance, it becomes possible for them to expect that those areas of the country that will appear to be most vulnerable to disruptions in the near future can be targeted in advance of those disruptions emerging into the open. In this index, resilience is defined less as the absence of threats to business stability yet more as the degree to which business ecosystems possess a positive capacity at a structural level that allows them to absorb shocks[17,18] as they occur.

1.1. Research Objectives

The primary objective of this study is to bridge the gap between static, annual economic indicators and the dynamic reality of disaster recovery by constructing a high-frequency metric of local economic durability[19]. Specifically, this research aims to:

- **Develop a Time-Sensitive Resilience Measure:** Build a new Business Resilience Index (BRI) at county-quarter resolution for the United States (2014-2024). Address the limitation of existing indices that only measure performance on an annual basis but do not capture the high-frequency changes that occur within a year that can impact post disaster recovery scenarios.
- **Integrate Multidimensional Infrastructure:** Synthesize diverse data sets to reflect the interconnected nature of resilience factors. This involves merging "hard" infrastructure data (federal flood insurance coverage and risk mitigation) with "soft" infrastructure data (community health, social determinants, and workforce characteristics).
- **Identify Latent Structural Dimensions:** Use Principal Component Analysis (PCA) to extract orthogonal dimensions of resilience from an extensive dataset of nearly 80

variables (Market Scale, Resilience Capacity, Safety/Risk Profile, Workforce Dynamics), minimizing researcher bias associated with feature selection.

- **Empirically Validate through Event Studies:** Assess the explanatory capacity of the BRI through a difference-in-differences event study[20] around major flood shocks (Texas 2015 and North Carolina 2018). The goal is to determine whether counties with higher pre-event BRI scores exhibit stronger labor market recovery than counties with lower BRI scores.
- **Assess Index Robustness:** Evaluate the stability of the index by comparing the "Statistical Index" (PCA variance-based) against a domain-driven "Strategic Index" to ensure that the core resilience signal persists across different weighting methodologies.

2. Data Sources and Preprocessing

2.1. Labor Market and Demographic Data

We extracted high-frequency local economic activity measures from the Quarterly Census of Employment and Wages (QCEW) dataset[21]. Key labor market metrics of interest included total quarterly employment counts (`Employment_Count_total`), total new hires (`New_Hires_total`), and weighted average earnings (`Earnings_wavg`). To account for varying market sizes, we constructed population denominators using resident population aggregates from the American Community Survey (ACS)[22], ensuring geographic consistency with QCEW reporting. Additionally, we calculated industry diversity metrics, such as `industry_diversity_emp` and `industry_effectiveN_emp`, to capture the structural complexity of local economies.

2.2. Health and Social Context

To characterize the socio-economic and health environment in which these businesses operate, we merged county-level annual indicators from the County Health Rankings (CHR)[23]. These features capture four dimensions of community resilience:

- **Health Behaviors:** Measures such as percentage of excessive drinking, adult obesity rates, and smoking prevalence.
- **Clinical Care:** Indicators including the primary care physicians rate, preventable hospitalization rate, and the percentage of the population that is uninsured.
- **Social and Economic Factors:** Contextual variables such as the percentage of children in poverty, income inequality ratios, violent crime rates, and social association rates.
- **Physical Environment:** Metrics assessing the built environment, including the percentage of severe housing problems, the food environment index, and driving death rates.

2.3. Flood Insurance Policy Data

We obtained policy-level data from the FEMA's FIMA NFIP Redacted Policies dataset[24]. The data were summarized from a policy-by-policy basis up to the county-quarter level to generate summary statistics relating to policy coverage and cost. Important aggregated features included:

- **Coverage and Costs:** Sums and means for building insurance coverage (`totalBuildingInsura`
contents coverage, and total insurance premiums.
- **Building Characteristics:** Counts for specific building descriptors—such as commercial buildings, single-family homes, and agricultural structures—and occupancy types.
- **Risk Mitigation:** Indicators for post-FIRM construction, elevated buildings, and flood-proofed structures (`floodproofedIndicator_mean`).

- **Valuation Ratios:** To assess insurance adequacy, we calculated the coverage-to-replacement cost ratio (`coverage_to_replacement_ratio`) and aggregated these ratios by occupancy type.

2.4. Disaster Event Data

Disaster impact data were obtained from the NOAA Storm Events Database[25]. The data were retrieved for 'Flood', 'Flash Flood', and 'Heavy Rain' events, occurring between 2014 and 2024. We summarized the data to the county-quarter, reported as property damage (`DAMAGE_PROPERTY`), crop damage (`DAMAGE_CROPS`), direct and indirect injuries, and fatalities.

2.5. Data Integration and Missing Value Treatment

The final dataset was constructed by sequentially merging the quarterly labor market panel with the FEMA policy data (matched on FIPS code) and the NOAA disaster data (matched on state and county names).

To address missing values and achieve panel balance, we employed a multi-stage imputation approach:

1. **Disaster Zero-Fill:** Missing observations in the disaster dataset were treated as non-event periods; consequently, null values for injuries, deaths, and damage variables were explicitly filled with zeros.
2. **Linear Interpolation:** For the broader panel variables, we grouped the data by State and County and sorted chronologically. We applied linear interpolation to bridge temporal gaps between reported quarters to propagate valid observations backward and forward to the edges of the time series.
3. **Final Cleanup:** Any remaining missing values—typically representing counties with no reported data for a specific metric across the entire timeframe—were filled with zero to ensure a complete dataset ready for analysis.

2.6. Feature Selection and Preprocessing

Following the data integration, we performed an explainable feature selection to further improve the interpretability of our final index. The original FEMA dataset contained a variety of features that were encoded as opaque numeric values (e.g., `occupancyType` codes 1.0 through 6.0 and various unmapped `buildingDesc` numeric codes). To ensure that the Business Resilience Index is interpretable to stakeholders, we discarded the raw opaque numeric feature set in favor of its descriptive equivalents (e.g., `buildingDesc_commercial_building_count`, `buildingDesc_single_family_count`). This step removed redundant or ambiguous columns, retaining only those features with clear, explainable links to business and physical resilience.

3. Methodology

To distill the multidimensional dataset into cohesive Business Resilience Index, we followed a rigorous statistical pipeline of feature selection, dimensionality reduction, and index weighting. This approach guarantees that the resulting index is based on the strongest latent factors present in the data and ignores the least essential and noise.

3.1. Feature Selection Pipeline

Starting with an initial set of **160 potential features**, the dataset was subjected to a four-stage filtration process to ensure data quality and model stability:

1. **Sparsity Thresholding:** We first removed features with extreme sparsity, defined as columns where zeros constituted more than 98% of observations. This step eliminated

39 variables with insufficient signal for cross-county comparison, reducing the feature set to 121.

2. **Variance Thresholding:** To ensure differentiability, we applied a variance filter to remove "quasi-constant" features. Variables were excluded if the same value appeared in more than 95% of the samples (threshold variance ≈ 0.0475). This removed an additional 9 low-variance columns, leaving 112 features.
3. **Collinearity Filtration:** To address multicollinearity, we computed the correlation matrix for the remaining features. For pairs of variables exhibiting a Pearson correlation coefficient greater than 0.95, one variable was dropped to reduce redundancy. This step removed 18 highly correlated columns, resulting in 94 features.
4. **Domain-Specific Pruning:** Finally, we performed a surgical removal of redundant ratio indicators (specifically overlapping coverage-to-replacement metrics) to ensure that technical artifacts did not inflate the importance of specific insurance categories. We force-dropped 15 redundant ratio columns, yielding a final feature count of 79 for the analysis.

3.2. Principal Component Analysis (PCA) and Dimensionality Strategy

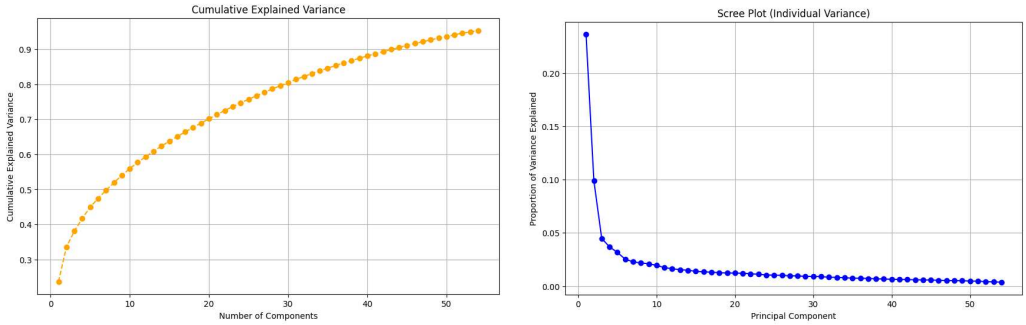
After feature selection, the resulting 79 features were scaled globally (across the entire data set) for the 2014-2024 time period before Principal Component Analysis. Although it's sometimes convenient to use cross-sectional scaling (i.e., scaling by quarter to account for temporal drift in time-series data) in some contexts[26], we deliberately chose to use a global scaling technique in this study because we believe it better preserves the absolute variance associated with longitudinal observations[27]. Natural disasters and other systemic shock events create absolute (rather than relative) burdens[28] on financial ecosystems. Therefore, measuring nominal changes in economic Market Scale (PC1) over time ensures that the index accurately reflects each county's expanded capacity for financial resilience as the system expands in nominal terms over time. Measuring economic growth at the macro/systemic level relative to the expanding baseline of each country allows us to accurately observe national systems' improvement (i.e., 'the rising tide' that lifts all boats) in baseline business resilience over time in a way that's not skewed by changes in other variables. To fully characterize the data structure, we initially decomposed the dataset to capture 95% of the cumulative variance. This exploratory diagnosis revealed that the dataset retains significant complexity, requiring 54 principal components to reach the 95% information threshold (Figure 1(**a**)).

The high dimensionality of the dataset suggests that the dataset is diverse but that much of the lower-order component variation (PC5 through PC54) is noisy and idiosyncratic rather than structural.

3.2.1. Component Selection and Index Construction

To determine the optimal dimensionality of the Business Resilience Index, we employed the Scree Test and validate the result semantically. We generated a scree plot of the eigenvalues to visualize the variance explained by each successive principal component.

As illustrated in Figure 1(**b**), the plot exhibits a distinct "elbow" at the fourth component, where the slope of the curve flattens significantly. Therefore, it can be inferred that the first four principal components contain the "signal" that the data is meant to convey, while all other components (PC5 through PC54) do not add significant power and are merely picking up noise and idiosyncrasies. Thus, we retained all principal components that captured approximately 40% of total variance.



(**a**) Cumulative Explained Variance (**b**) Scree Plot of Eigenvalues

Figure 1. Component Selection Diagnostics. Panel (a) illustrates that these first four components collectively explain approximately 40% of the total systemic variance. Panel (b) displays the scree plot, showing a distinct elbow after the fourth principal component.

While this selection excludes the "tail" of the variance distribution, we justify this decision on two key grounds:

1. **Signal-to-Noise Ratio:** The leading components capture broad, robust economic and physical structures that generalize across the nation. The subsequent components increasingly capture localized artifacts and measurement noise which do not represent reliable indicators of general resilience.
2. **Interpretability:** The top four components map cleanly to interpretable policy domains: Market Scale (PC1), Resilience Capacity (PC2), Safety/Risk Profile (PC3), and Workforce Dynamics (PC4). There is no motivation to include additional components that would diminish semantic meaning of the index and fail to add value proportional to its impact on ranking stability.

This selection strategy prioritizes structural interpretability and stability over the maximization of total variance, ensuring the final index reflects robust national trends rather than overfitting to minor local variations.

3.2.2. Weighting Strategy

The final Strategic Index was calculated as a weighted sum of the four normalized sub-scores. Rather than relying on the structural variance of the data alone, however, the weights were determined with reference to domain-specific priorities that target the most critical elements for sustainability. Most specifically, the strategy gives its highest weighting to resilience and scale:

$$\text{Strategic Index} = 0.40(\text{Resilience}) + 0.30(\text{Scale}) + 0.15(\text{Safety}) + 0.15(\text{Workforce})$$

Another key property of this weighting scheme is its relationship to the time-series structure of the data. Since the principal components were standardized across the globe and across time-periods of the 2014-2024 panel, the dimension Market Scale (PC1) is consequently expected to have lower nominal values in early time-periods, for example the 2015Q2 Texas event study in Section 5. Thus, application of these static strategic weights will result in the index being mathematically more sensitive to Socioeconomic Resilience (PC2) in historical quarters relative to Market Scale, whose proportional influence, however, increases over time.

We choose to retain this temporal asymmetry. From the perspective of business continuity, absolute levels of capital and insurance density can serve as structural buffers against external events. Thus, in earlier years when these capital buffers would have had lower nominal values, local recovery would have theoretically depended more on

the baseline socioeconomic and health capacity of its workforce. By retaining a global scaling approach, the index accurately captures this reality and shows how local recovery increasingly depends on "hard" capital scales versus "soft" community infrastructure over time.

3.2.3. Sensitivity Analysis and Robustness Checks

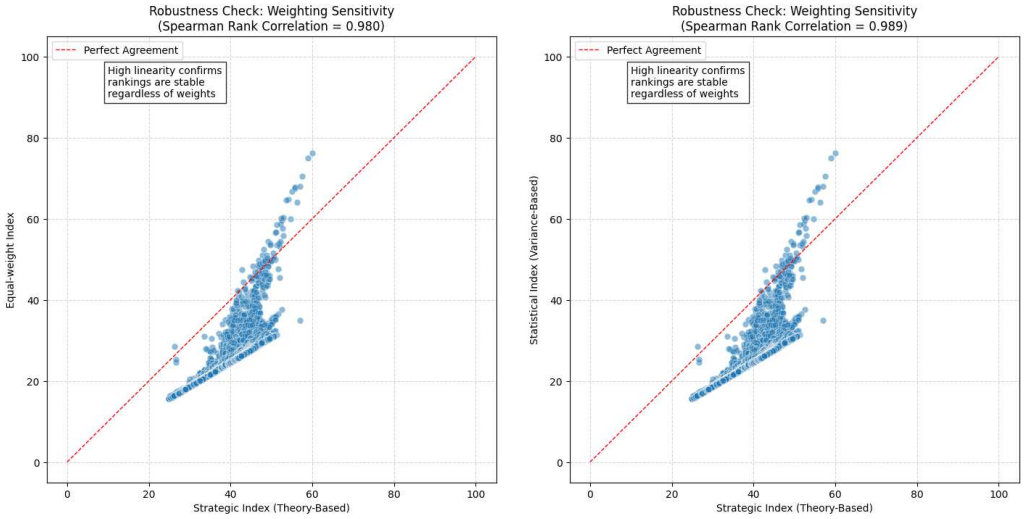
To validate the stability of the Strategic Index and ensure our domain-driven assumptions did not heavily skew the results, we conducted a sensitivity analysis by comparing it against two alternative aggregation methods[13]:

1. **Equal Weight Index:** Assigns a fixed 25% weight to each of the four sub-scores, serving as a neutral baseline[14].
2. **Statistical Index:** Applies data-driven weights derived from the *relative* variance explained among the retained principal components. This method calculates weights as $W_i = \frac{\lambda_i}{\sum_{k=1}^{4} \lambda_k}$ (where the denominator is the cumulative variance of the selected components), ensuring the score is driven entirely by the underlying data structure.

We applied Spearman Rank Correlation to assess the concordance of the rankings[29] provided by the Statistical and Strategic Indices, focusing on the stability of the relative rankings (i.e. the identification of relative "top performers" rather than the absolute values of the scores). Such a metric is particularly suitable for capturing the maintaining of the index's core message despite the choice of weighting approach.

The region of the scatterplot showing the concordance of the two indices shows a sharp linear edge along the leftmost distribution from the origin, corresponding to the minimal market size of a minimal number of counties, for which the calculated resilience indices are linearly related due to the paucity of other contributing socioeconomic factors relative to total capital volume. However, as the market size of each county increases beyond minimum required for exchange monitoring, the points diverge from this linear edge, displaying an exaggerated fan-out from left to right over the upper right quadrant of the scatterplot. The graphic demonstration of this fan-out reveals the "sensitivity" of the Statistical Index (which utilized a larger variety of contributing capital types and factors (56.7%)) relative to Strategic Index (with its more-balanced weighting approach utilizing the factors and types of capital that impact market resilience (30.0%)). Thus, the adjustment to a Strategic Index weighting scheme does prevent an abnormal exaggeration of effects due to a nominal large market size from obscuring true socioeconomic weaknesses from manifesting as a lack of resilience.

Spearman Rank Correlations showed that the methods were congruent with one another. The strategic index had high correlation values with the statistical index ($\rho = 0.989$) and the equal-weighted index ($\rho = 0.980$)). Both values were above 0.97, so the index is insensitive to weighting schemes. The ranks of the counties are the same whether one uses mathematical or theoretical weighting to arrive at the strategic weights.



(**a**) Strategic Index vs. Equal-Weight Index (**b**) Strategic Index vs. Statistical Index

Figure 2. Robustness Check: Weighting Sensitivity. Panel (a) compares the domain-driven Strategic Index against a neutral Equal-Weight baseline, demonstrating strong agreement with a Spearman rank correlation of $\rho = 0.980$. Panel (b) compares the Strategic Index against a purely data-driven Statistical Index, revealing a near-perfect correlation of $\rho = 0.989$.

3.3. Event-Study Validation with BRI Heterogeneity

3.3.1. Event-time construction and analysis window

To assess whether the Business Resilience Index (BRI) operates as a meaningful measure of resilience under acute stress, we estimate a matched difference-in-differences event study around two major flood-related episodes: *Texas 2015Q2* and *North Carolina 2018Q3*. The exercise is not intended to recover causal mechanisms attributable to the index itself. Instead, it evaluates a sharp, testable implication: conditional on comparable exposure and baseline characteristics, counties with higher pre-event BRI should follow a stronger post-event employment path than counties with lower pre-event BRI.

For each state-event pair, we limit the sample to counties within the affected state and define event time in quarters relative to the event quarter:

$$\text{rel_}q_{it} = (4 \cdot \text{Year}_t + (\text{Quarter}_t - 1)) - (4 \cdot \text{Year}^* + (\text{Quarter}^* - 1)), \tag{1}$$

where $(\text{Year}^*, \text{Quarter}^*)$ denotes the event quarter. We target a symmetric window of $[-8, +7]$ quarters; when an event occurs near the start of the panel, the pre-period is necessarily shorter, and we use the maximal set of available pre-event quarters. The baseline period is normalized to $\text{rel_}q = -1$, so all dynamic coefficients are interpreted relative to the quarter immediately preceding the event. Because the county-quarter panel begins in 2014Q1, early events can imply a truncated pre-period even when the intended window is symmetric. For Texas 2015Q2, the realized pre-event window is 2014Q1 to 2015Q1 (that is, $\text{rel_}q \in [-5, -1]$), while the post-event window remains observed through $\text{rel_}q = +7$. All event-time indicators and joint lead tests are computed over the realized set of observed pre-event quarters; for transparency, we report the realized $\text{rel_}q$ range used for each case in the results.

3.3.2. Disaster exposure measurement and treatment/control definitions

Disaster exposure is measured using county-quarter flood damage aggregated from storm event records. We define *event-quarter damage* as total recorded flood damage for county i in the event quarter, and we define *window damage* as the sum of damages over

the full analysis window[30]. The baseline treatment definition selects the N counties with the largest strictly positive event-quarter damage within the state (top-N, with $N = 20$ in the main specification), thereby concentrating attention on counties experiencing the most salient shock intensity in the event quarter.

The control pool is constructed to minimize contamination from smaller contemporaneous shocks. In the main specification, we use *strict controls*: counties with zero recorded damage in the event quarter and zero recorded damage anywhere in the full analysis window. This restriction limits the risk that controls include counties affected by smaller events that would mechanically attenuate estimated treatment effects[31].

3.3.3. Pre-event BRI and heterogeneity strata

To anchor heterogeneity in pre-determined conditions, we define each county's pre-event resilience as the mean BRI over all pre-event quarters in the window (those with rel_$q \leq -1$), denoted BRI_pre$_i$. We then form High-BRI and Low-BRI strata using a median split of BRI_pre$_i$ among treated counties. This choice yields treated groups of comparable size while preserving the interpretation of high versus low resilience within the exposed set. Controls are assigned to strata using the same threshold so that comparisons remain within broadly similar resilience environments.

3.3.4. Matched design and covariates

Because the most exposed counties can differ systematically from unexposed counties, we apply nearest-neighbor matching to improve comparability prior to estimating dynamic effects[32]. Each treated county is matched to $k = 2$ controls using Euclidean distance in a standardized covariate space[33]. The matching variables are chosen to capture both pre-event *levels* and pre-event *trajectories* of local labor-market conditions:

- **Pre-event outcome path:** a vector of pre-event log employment values over the available pre-period quarters (within the analysis window), together with a pre-event slope summary[34] that captures trend direction.
- **Baseline economic structure:** pre-event averages of population, hiring rates, and industry diversity measures.

All matching covariates are z-scored prior to distance computation to avoid scale-driven dominance. To reduce sensitivity to poor matches, we impose a caliper rule: treated counties whose closest control exceeds a threshold distance are excluded from the matched sample. In the main implementation, the caliper is chosen using a high quantile of treated counties' nearest-neighbor distances, which retains most treated counties while trimming extreme outliers.

Matching is performed *without replacement*, so a given control county is not reused as a comparison for multiple treated counties. We also implement an optional *stratified matching* variant aligned with the heterogeneity design: High-BRI treated counties are matched only to High-BRI controls, and Low-BRI treated counties are matched only to Low-BRI controls. This restriction strengthens interpretability by ensuring that High versus Low comparisons are not mechanically driven by systematic differences in the control pool across strata.

3.3.5. Estimation: two-group event study with fixed effects and population weights

Let y_{it} denote the labor-market outcome for county i in quarter t. The primary outcome is log employment, which supports approximate percent interpretations. Using the matched

sample, we estimate an event-study specification with county and quarter fixed effects and separate dynamic paths for High-BRI and Low-BRI treated groups:

$$y_{it} = \alpha_i + \lambda_t + \sum_{k \neq -1} \beta_k^H (\mathbb{1}\{\text{HighBRI_treated}_i\} \cdot \mathbb{1}\{\text{rel_}q_{it} = k\}) + \sum_{k \neq -1} \beta_k^L (\mathbb{1}\{\text{LowBRI_treated}_i\} \cdot \mathbb{1}\{\text{rel_}q_{it} = k\}) + \varepsilon_{it}. \quad (2)$$

County fixed effects α_i absorb time-invariant differences across counties, while quarter fixed effects λ_t capture common shocks and seasonality. The coefficients β_k^H and β_k^L trace the dynamic deviation of treated counties from their matched controls at event time k, separately by resilience stratum.

We estimate the model by weighted least squares using pre-event population as an analytic weight. This choice places greater emphasis on labor-market changes in larger counties[35] while retaining county-level identification through fixed effects. Standard errors are clustered at the county level to account for serial correlation within counties across quarters.

For log outcomes, we report coefficients in log points and, where useful, translate them into percent effects using:

$$\%\Delta y \approx 100 \cdot (\exp(\beta) - 1). \quad (3)$$

3.3.6. High-Low contrasts and pre-trend diagnostics

A primary object of interest is the *High-Low difference* at each event time k, $\beta_k^H - \beta_k^L$, which summarizes whether higher resilience is associated with systematically stronger recovery conditional on exposure and matching. We report this difference along with its standard error (constructed from the full clustered covariance matrix) and the corresponding Wald test p-value[36].

To evaluate differential pre-period dynamics, we conduct joint lead tests over all pre-event coefficients with $k \leq -2$ for (i) High-BRI treated leads, (ii) Low-BRI treated leads, and (iii) the set of High-Low lead differences. These tests are reported as diagnostics: they indicate whether post-event divergence is accompanied by detectable pre-period separation within the matched sample.

3.3.7. Complementary matched-sample specifications

To connect quarter-by-quarter dynamics with more aggregated recovery measures, we also estimate matched-set models in a county-level cross section. Using the matched sample, we compute each county's mean outcome in the pre-period and post-period and define Δy_i as the post-minus-pre change. We then estimate:

$$\Delta y_i = \gamma_s + \theta \cdot \text{Treated}_i + \phi \cdot (\text{Treated}_i \times \text{BRI}_i) + u_i, \quad (4)$$

where γ_s are matched-set fixed effects. An ANCOVA variant replaces Δy_i with the post-period mean and controls for the pre-period mean.[37] These specifications are not intended to replace the event study. Instead, they provide a compact check on whether the same moderation pattern appears when recovery is summarized as an average shift rather than traced quarter by quarter.

4. Results

4.1. Principal Component Analysis

The application of Principal Component Analysis to the standardized feature set successfully distilled the multidimensional data into four primary orthogonal components.

These components, collectively accounting for roughly 40% of the total variance, represent the distinct structural pillars of local business resilience: Market Scale, Socioeconomic Resilience, Urban Density Risk, and Industrial Economy Profile.

Table 1. Principal Component Analysis (PC1–PC4) Loadings

Component	Type	Feature Variable	Loading
PC1	Positive	buildingDesc_other_count	0.2150
		policyCount_sum	0.2130
		totalInsurancePremiumOfThePolicy_sum	0.2076
		buildingDesc_detached_guest_count	0.2007
		buildingDesc_warehouse_count	0.1991
	Negative	% Adults with Obesity	-0.0401
		% Smokers	-0.0349
		Social Association Rate	-0.0292
		Teen Birth Rate	-0.0202
		% Drive Alone to Work	-0.0198
PC2	Positive	% Children in Poverty	0.3149
		% Fair or Poor Health	0.3124
		Physically Unhealthy Days	0.2872
		Teen Birth Rate	0.2598
		% Smokers	0.2424
	Negative	% Some College	-0.2702
		Food Environment Index	-0.2314
		% Excessive Drinking	-0.2261
		% With Access to Exercise Opportunities	-0.1477
		Primary Care Physicians Rate	-0.1288
PC3	Positive	totalBuildingInsuranceCoverage_mean	0.2996
		% Severe Housing Problems	0.2967
		Violent Crime Rate	0.2648
		% With Access to Exercise Opportunities	0.2519
		industry_effectiveN_emp	0.2505
	Negative	Social Association Rate	-0.1754
		buildingDesc_apartment_unit_count	-0.0991
		buildingDesc_apartment_unit_cov_sum	-0.0805
		buildingDesc_apartment_unit_repl_sum	-0.0777
		% Adults with Obesity	-0.0685
PC4	Positive	Preventable Hospitalization Rate	0.3552
		Mentally Unhealthy Days	0.3389
		% Adults with Obesity	0.2795
		Earnings_wavg	0.2231
		% Long Commute - Drives Alone	0.2152
	Negative	% Uninsured	-0.2639
		buildingDesc_agricultural_count	-0.2198
		buildingDesc_agricultural_cov_sum	-0.1983
		% Unemployed	-0.1821
		Teen Birth Rate	-0.1690

4.1.1. PC1: Market Size (The "Volume Dial")

The first principal component (PC1) is a unidirectional measure of the absolute size of the local insurance market. The top positive predictors are only related to volume: `buildingDesc_other_count` (+0.215), `policyCount_sum` (+0.213), and `totalInsurancePaid_sum` (+0.208). The negative predictors are unremarkable (e.g., `% Adults with Obesity` at -0.040), showing that this predictor does not represent a trade-off but magnitude. A high score on PC1 simply indicates that a county has a large physical

insurance market with a great deal of built asset volume compared to other counties, distinguishing major economic hubs from small markets with limited development.

4.1.2. PC2: Socioeconomic Resilience (The "Distress Dial")

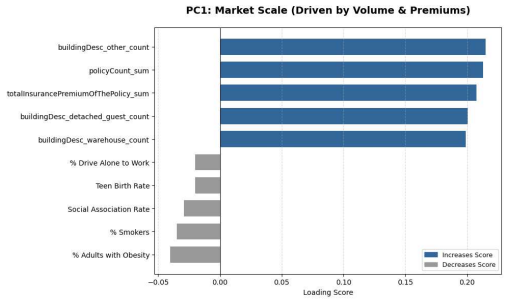
The second principal component (PC2) reflects the socioeconomic resilience of the local market, opposing predictors of distress to predictors of well-being. In its raw form, the positive predictors were dominated by indicators of vulnerability to `% Children in Poverty` (+0.315), `% Fair or Poor Health` (+0.312), and `Teen Birth Rate` (+0.260). Indicators of resilience included access to care (-0.129) (`Primary Care Physicians this component to the Business Resilience Index (where a high score must reflect a positive outcome), Rate`) and education (-0.270) (`% Some College`). To reorient we inverted the polarity of PC2 (multiplied by -1). In the final index, a high score on this dimension reflects a community with strong public health, low poverty rates, and high human capital investment.

4.1.3. PC3: Urban Density Risk (The "Big City" Paradox)

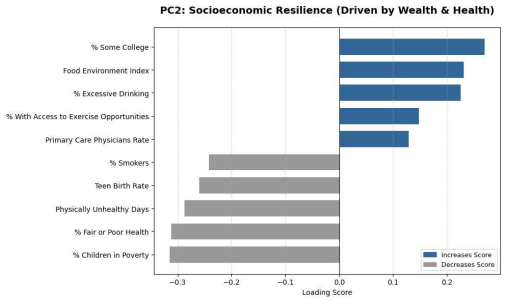
The third principal component (PC3) identifies the specific risk profile of densely populated urban areas. The component includes a combination of high asset values and social stress indicators. The positive predictors include `totalBuildingInsuranceCoverage_mean` (+0.300) and `industry_effectiveN_emp` (+0.250), which indicate a wealthy and diverse economy. However, these predictors are also co-located with `Violent Crime Rate` (+0.265) and `% Severe Housing Problems` (+0.297). This component distinguishes between Dense City Centers (high PC3 scores) that have high capital values but also high operational friction and Rich Suburbs or rural areas (low PC3 scores) that have similar levels of wealth but none of the challenges associated with density.

4.1.4. PC4: Industrial vs. Agricultural Economy

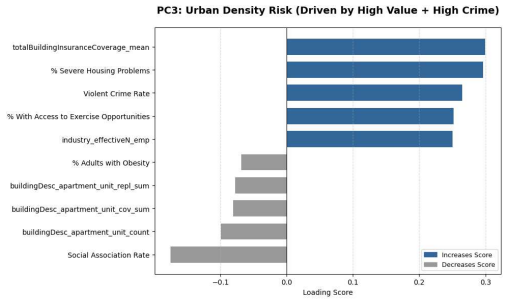
The fourth principal component (PC4) distinguishes between industrial/service-based economies and agricultural/rural economies. The positive predictors include higher average earnings (`Earnings_wavg`, +0.223), higher levels of diversity in commuting patterns (`% Long Commute`, +0.215), but also indicators of lifestyle-related health issues (`Preventable Hospitalization Rate`, +0.355; `% Adults with Obesity`, +0.279). The negative predictors include strong associations with the agricultural sector (`buildingDesc_agricultural_count`, -0.220) and other indicators of rural instability, such as `% Uninsured` (-0.264) and `% Unemployed (-0.182)`. This dimension captures the structural features of the local economy, distinguishing between modernized industrial areas with higher wages but higher stress levels and more traditional agricultural economies.



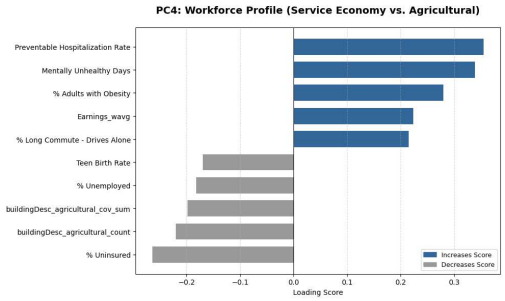
(**a**) PC1: Market Scale (Volume)



(**b**) PC2: Socioeconomic Resilience



(**c**) PC3: Urban Density Risk



(**d**) PC4: Industrial vs. Agricultural

Figure 3. Loadings of the Top Four Principal Components. Top 10 features driving each dimension. (a) PC1 is driven by insurance volume; (b) PC2 contrasts poverty against health access; (c) PC3 captures the high-wealth/high-crime paradox of urban centers; (d) PC4 differentiates industrial labor markets from agricultural ones.

4.2. Index Exemplars in the Event Quarter

To illustrate the creation of a composite index, we examine index exemplars throughout quarters in which localized severe weather events occurred. We examine the case of Texas during 2015Q2 and North Carolina during 2018Q3, two jurisdictions and time periods that corresponded with particularly catastrophic hurricane- and storm-related events that had severely impacted localized economic areas.

In particular, during 2015Q2, Texas experienced record-breaking Memorial Day floods and the impact of Tropical Storm Bill, which caused historic flooding, river overflow, and state-wide disaster declarations. In the case of 2018Q3, Hurricane Florence made landfall in North Carolina as a catastrophic slowly-moving storm that dropped trillions of gallons of rain, causing unprecedented levels of freshwater flooding and catastrophic infrastructure failures along the eastern seaboard.

The top and bottom five counties for the Business Resilience Index (BRI) in the event quarter for Texas and North Carolina are provided in Tables 2 and 3. The indices are also rendered as heat maps that display our calculated resilience index for each county in Figures 4(**a**) and 4(**b**). Together, the information presented in these tables and figures illustrate the wide within-state variability of resilience scores, especially with regard to how vulnerability can vary greatly even within close proximity to one another between two counties facing equivalent meteorological threats.

In particular, these exemplars demonstrate the economic and geographical differences that the Business Resilience Index has captured regarding these two jurisdictions, and they provide important anchors for the additional iteration of the case study analysis presented in Section 5, where we will describe in detail the post-disaster recovery processes that each of these particular set of regions underwent.

Table 2. Texas 2015Q2 Top and Bottom 5 Counties by PC Scores and Index

Rank	County	PC1	PC2	PC3	PC4	Index
Highest 5	Collin	1.515	76.201	35.516	59.809	45.234
	Williamson	1.243	74.601	37.600	60.578	44.940
	Carson	0.548	71.840	43.181	62.866	44.807
	Rockwall	0.865	73.528	39.052	61.400	44.739
	Roberts	0.379	71.266	47.016	59.566	44.607
Lowest 5	Limestone	0.433	40.533	39.241	62.521	31.607
	Zavala	0.581	38.041	37.462	57.332	29.610
	Willacy	0.659	36.704	37.069	58.913	29.277
	Brooks	0.461	35.603	38.196	59.093	28.973
	Starr	0.470	35.349	40.247	57.250	28.905

Table 3. North Carolina 2018Q3 Top and Bottom 5 Counties by PC Scores and Index

Rank	County	PC1	PC2	PC3	PC4	Index
Highest 5	Wake	2.725	75.373	34.618	62.329	45.509
	Orange	1.161	74.185	35.974	61.142	44.590
	Union	1.306	70.887	37.860	63.539	43.956
	Mecklenburg	3.231	69.833	33.446	61.424	43.133
	Buncombe	1.932	68.797	36.899	60.928	42.773
Lowest 5	Edgecombe	0.967	46.227	37.052	61.521	33.567
	Northampton	0.505	45.483	38.452	62.138	33.433
	Halifax	0.628	45.655	36.783	61.925	33.257
	Scotland	0.661	43.869	36.408	61.099	32.372
	Robeson	1.167	40.894	36.619	62.890	31.634

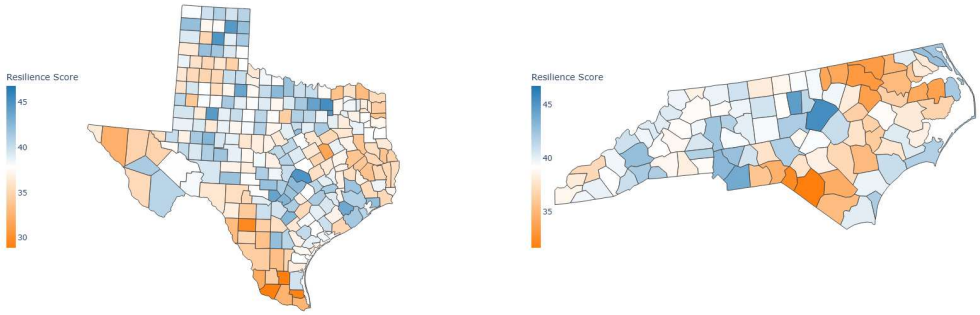
5. Case Study: Linking Event-Study Dynamics to Spatial BRI Patterns

The two cases, Texas 2015Q2 and North Carolina 2018Q3, serve as stress tests of whether the index behaves as a resilience measure in practice. Put concretely, among exposed counties (the treated group) and a matched set of comparable controls, do counties with higher BRI exhibit stronger post-event labor-market outcomes? We interpret the resulting dynamics in light of the within-state spatial distribution of BRI in the event quarter, focusing on structural differences in market scale, socioeconomic resilience capacity, and the broader risk and workforce profile captured by the index.

5.1. Statewide BRI spatial patterns in the event quarter

Before turning to dynamic treatment effects, we use the county-quarter BRI maps to clarify what "high" and "low" resilience look like within each state. Figures 4(**a**) and 4(**b**) plot the BRI level in the event quarter for all counties in Texas (2015Q2) and North Carolina (2018Q3). The maps are not restricted to treated counties; instead, they provide a statewide baseline for interpreting heterogeneity and make clear that resilience is spatially clustered rather than randomly distributed.

Two points help guide interpretation. First, because PC1 (market scale) contributes materially to the composite score, counties that anchor large labor markets and insurance footprints tend to appear in the upper tail of the distribution. Second, the index is not reducible to "urban equals resilient." The non-scale components (socioeconomic resilience, density risk, and labor-market structure) generate substantial dispersion among places that are similar in size. For this reason, the maps should be read as a joint reflection of scale and capacity, which is precisely what makes them useful for qualitative interpretation alongside the event-study estimates.



(**a**) 2015Q2 Texas Index (**b**) 2018Q3 North Carolina Index

Figure 4. Regional Index Comparisons. Comparison of the calculated index for Texas counties in 2015 and North Carolina counties in 2018.

5.2. Event-study evidence with BRI heterogeneity

Figure 5 reports event-study estimates stratified by BRI (HighBRI vs. LowBRI) relative to matched control counties. The outcome is measured in log employment (log points), so coefficients can be interpreted approximately as percent deviations from the counterfactual path (for example, $\exp(\beta) - 1$). The event quarter is normalized with baseline rel_$q = -1$, and error bars show 95% confidence intervals clustered at the county level.

The key empirical result is not merely that treated counties respond to the shock. Rather, treated counties with higher pre-event BRI separate systematically from treated counties with lower pre-event BRI. This pattern matches the conceptual role of the index: HighBRI counties are expected to combine thicker labor markets, greater sectoral diversity, larger insured asset bases, and stronger community health and human-capital conditions that facilitate business continuity and reallocation during recovery.

5.2.1. Texas 2015Q2: persistent post-event divergence

In Texas, the post-event trajectories display a clear and sustained separation between HighBRI and LowBRI treated counties (Figure 5a). The pattern is economically meaningful in both sign and magnitude. Table 4 summarizes representative event-time estimates: HighBRI treated counties move to positive deviations after the shock and continue rising over subsequent quarters. LowBRI treated counties, by contrast, remain near zero in the event quarter and become persistently negative thereafter.

By $k = 6$, HighBRI counties are approximately $+5.4\%$ above their matched controls (0.0526 log points), while LowBRI counties are about -1.8% below controls (-0.0185 log points). The implied High-Low difference at $k = 6$ is 0.0712 log points (about a 7.4% gap), statistically distinct from zero. This profile is consistent with a resilience mechanism: higher-BRI places appear to re-stabilize employment more quickly and to sustain stronger medium-run recovery dynamics, rather than exhibiting only a short-lived rebound.

At the same time, the joint lead tests point to an important nuance. Although HighBRI leads are not jointly significant in Texas, LowBRI leads and High-Low lead differences show evidence of pre-period divergence. In a case-study setting, we treat this not as a failure of the measure, but as a reminder that resilience is partly structural and can manifest in differential baseline dynamics even before the shock. The core validation signal remains the post-event widening gap between strata under a matched design that improves comparability.

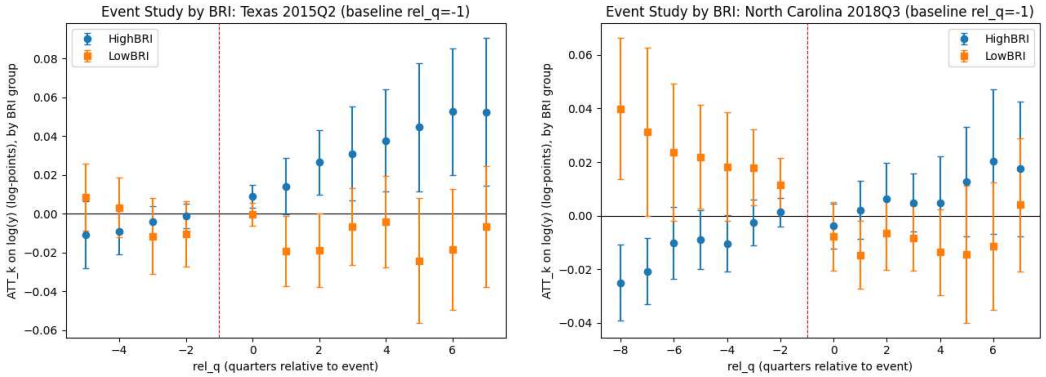
5.2.2. North Carolina 2018Q3: delayed but consistent separation

North Carolina shows a smaller and more gradual separation (Figure 5b), consistent with recovery shaped by prolonged disruption, staggered reopening, and slower labor-market adjustment in the most exposed areas. As reported in Table 5, the High-Low difference becomes statistically meaningful one quarter after the event ($k = 1$) and remains positive into the medium run. By $k = 6$, HighBRI counties are about $+2.0\%$ above matched controls (0.0203 log points), while LowBRI counties are roughly -1.1% below controls (-0.0115 log points), implying a High-Low gap of 0.0318 log points (about 3.2%).

Pre-event lead coefficients are more pronounced in North Carolina than in Texas, and the joint lead tests indicate non-trivial pre-period differences. Even so, the dynamics remain informative for validating the BRI: post-event coefficients move in the direction predicted by the index, with HighBRI counties stabilizing earlier and maintaining a higher employment path relative to controls than LowBRI counties.

5.2.3. Synthesis: what heterogeneity is telling us in a case-study frame

Across both cases, the event study delivers the same qualitative message: HighBRI counties exhibit stronger post-event employment performance than LowBRI counties, conditional on exposure and matched comparability. The magnitude differs by state and episode, as expected given variation in local industrial structure, disaster footprint, and the time profile of disruption. Importantly, the contrast is visible not only in point estimates but also in the shape of recovery: HighBRI trajectories turn upward sooner and remain above LowBRI trajectories as the horizon extends.



(a) Texas 2015Q2 **(b)** North Carolina 2018Q3

Figure 5. Event-study estimates by BRI stratum relative to matched controls. Error bars show 95% confidence intervals using county-clustered standard errors.

Table 4. Texas 2015Q2 event-study estimates by BRI stratum (baseline rel_$q = -1$).

rel_q	High-BRI β_k^H	Low-BRI β_k^L	High-Low $(\beta_k^H - \beta_k^L)$	p_{diff}
-2	-0.0013 (0.0032)	-0.0106 (0.0086)	$+0.0093$ (0.0085)	0.2801
0	$+0.0088$ (0.0030)	-0.0004 (0.0030)	$+0.0092$ (0.0015)	0.0000
2	$+0.0264$ (0.0085)	-0.0189 (0.0096)	$+0.0453$ (0.0082)	0.0000
6	$+0.0526$ (0.0166)	-0.0185 (0.0159)	$+0.0712$ (0.0113)	0.0000

Table 5. North Carolina 2018Q3 event-study estimates by BRI stratum.

rel_q	High-BRI β_k^H	Low-BRI β_k^L	High-Low $(\beta_k^H - \beta_k^L)$	p_{diff}
0	-0.0039 (0.0042)	-0.0077 (0.0065)	$+0.0038$ (0.0069)	0.5862
1	$+0.0021$ (0.0055)	-0.0146 (0.0064)	$+0.0167$ (0.0067)	0.0159
6	$+0.0203$ (0.0138)	-0.0115 (0.0121)	$+0.0318$ (0.0139)	0.0267

Table 6. Joint lead tests ($k \leq -2$) for event-study coefficients.

Case	High-BRI leads	Low-BRI leads	(High-Low) leads
Texas 2015Q2	0.2838	0.0098	6.24×10^{-14}
North Carolina 2018Q3	0.0011	0.0040	1.43×10^{-5}

5.3. Qualitative interpretation: county contrasts and within-state index gradients

The event study shows that BRI stratification is associated with distinct post-event employment dynamics. The next question is why this separation is plausible at the county level. We address this by pairing the statewide BRI maps with representative counties from the top and bottom of the distribution (Tables 2 to 3) as qualitative anchors. The aim is not to suggest that every high-BRI county is insulated from disruption or that every low-BRI county lacks adaptation. Rather, the goal is to show that the index corresponds to recognizable structural differences across places that can shape recovery capacity[38].

5.3.1. Texas: a metro-corridor resilience gradient versus peripheral vulnerability

Texas exhibits a pronounced spatial gradient in BRI (Figure 4(**a**)). Higher scores cluster around major labor-market corridors[39] and suburban rings, where employment bases are larger and more diversified[40], insured asset density is higher, and workforce and health indicators are generally stronger. This pattern is consistent with the upper tail of the Texas distribution in 2015Q2 (Table 2), where counties such as Collin, Williamson, and Rockwall sit within large, integrated metro economies.

The lower tail of the Texas distribution includes counties such as Starr, Brooks, Willacy, and Zavala (Table 2), which differ structurally in ways the index is designed to capture: smaller markets, thinner employment bases, and socioeconomic constraints[41] reflected in the resilience-capacity dimension. In these settings, alternative employers are fewer, commuting-based substitution is more limited, and small-business cash-flow vulnerability[42] becomes more binding. These mechanisms are consistent with the persistently negative post-event path observed for LowBRI treated counties in the event study.

5.3.2. North Carolina: urban centers versus capacity-constrained counties

North Carolina's BRI map (Figure 4(**b**)) shows a clear contrast between high-scoring urban and amenity-driven counties and lower-scoring counties concentrated in parts of the eastern and southeastern state. This spatial structure aligns closely with the high- and low-BRI county lists in 2018Q3 (Table 3). Wake, Orange, Mecklenburg, and Union represent major employment centers with strong institutional capacity and diversified industry composition, while Edgecombe, Northampton, Halifax, Scotland, and Robeson sit in the lower tail where the index indicates weaker baseline capacity.

This qualitative lens helps explain why North Carolina's separation is smaller but still meaningful. Many high-BRI counties are anchored by thicker labor markets and stronger baseline capacity, while low-BRI counties face compounding constraints that can slow reopening and rehiring (for example, thinner labor markets, higher poverty burdens[43], and weaker health capacity). The event-study results reflect these differences in recovery trajectories, with HighBRI counties stabilizing earlier and maintaining a higher employment path[44] relative to controls than LowBRI counties.

6. Discussion

The Business Resilience Index (BRI) condenses into a single summary statistic the slow-moving structural features that shape how local business environments absorb disruption and return to baseline after a shock. The PCA results underscore why any single proxy such as income, unemployment, or even flood exposure in isolation cannot capture this

multidimensional capacity. *Market scale* reflects the size of the insured asset base and the breadth of local economic activity, while the remaining components separate *capacity* from *scale*: baseline socioeconomic and health conditions, density-related operational frictions, and the underlying structure of the labor market.

The validation exercises then ask a more consequential question: do these structural differences map into systematically different recovery paths when counties experience acute flood shocks? The answer is consistent in Texas 2015Q2 and North Carolina 2018Q3. Conditioning on exposure and using a matched comparison set, high-BRI treated counties generally stabilize earlier and exhibit a stronger post-event employment trajectory than otherwise comparable low-BRI treated counties. The timing and magnitude are not identical across the two settings, which is what one would expect given differences in event footprints, industrial composition, and the speed with which disruption translates into labor-market adjustment. What remains common, however, is the *shape* of the response: a post-event divergence that lines up with pre-event differences in resilience.

6.1. What the index adds beyond exposure metrics

A central implication is that exposure and recovery capacity should not be treated as substitutes. Exposure indicates where shocks are likely to occur; the BRI helps identify where recovery is likely to be slow *conditional on exposure*. That distinction is operationally important for the allocation of scarce resources. In large, high-scale counties, even small proportional losses can imply sizable aggregate employment effects, making rapid infrastructure restoration and coordination particularly valuable. In smaller counties with limited resilience capacity, the constraint is more often the mechanics of continuity and rehiring, such as credit access, administrative frictions, workforce constraints, and disruptions to household stability, so targeted stabilization efforts may yield higher marginal returns than responses calibrated primarily to aggregate volume.

6.2. Interpreting heterogeneity without over-claiming

These event studies are informative because they align three elements: a pre-specified index, a clearly defined event window, and a comparison group rendered more similar through matching. At the same time, the lead tests show that some pre-period separation persists for parts of the matched sample, which argues against interpreting the dynamic coefficients as the causal effect of flood exposure alone. In this context, the BRI is best understood as a classifier of baseline capacity and risk, useful for anticipating recovery challenges and structuring monitoring, rather than as a tool designed to isolate a single mechanism. This framing matches the index's purpose: it aggregates slow-moving structural factors that can shape both pre-event dynamics and post-event adjustment.

6.3. Operational use cases

Two practical applications follow.

Preparedness targeting. Because the BRI is constructed from pre-event information, it can support tiered preparedness within a state. High-scale counties may warrant planning that prioritizes minimizing cascading spillovers and limiting downtime in major employment corridors. Lower-capacity counties may warrant measures aimed at reducing barriers to reopening and rehiring, for example, small-business continuity support, streamlined relief access, and workforce stabilization policies that address health-related constraints and displacement.

Recovery monitoring. After an event, the BRI can be used to define risk strata for tracking whether recovery programs are narrowing gaps in labor-market outcomes. In that role, the index complements evaluation by providing a principled way to identify places

where recovery has historically lagged and to prioritize outreach when observed outcomes begin to drift away from expected trajectories.

Taken together, the results indicate that resilience can be measured in a way that is interpretable and empirically linked to recovery dynamics. The index is not a substitute for event-specific context; rather, it provides a consistent baseline for comparing counties and for anticipating where post-disaster employment losses are most likely to persist.

7. Limitations and Future Directions

As a composite index constructed from heterogeneous administrative sources, the Business Resilience Index (BRI) reflects both underlying signal and specific modeling trade-offs. Several predictors are observed on a yearly frequency (e.g., CHR), while others are binned quarterly (QCEW and FEMA aggregates). Constructing a county-quarter panel therefore requires interpolation or "carry-forward" assumptions that may smooth local shocks relative to national averages. Disaster exposure is measured by recorded damage, which introduces potentially noisy and cross-county attribution errors; while our strict control definition minimizes contamination, it also limits the control pool and match quality for specific states or events. More generally, standard preprocessing procedures—such as zero-filling non-event periods, winsorization, and log transformations—stabilize the index but may dampen the tail behavior of smaller counties.

An additional trade-off of the global scaling approach is the presence of longitudinal time bias in the Market Scale component (PC1). Because standardization is performed across a ten-year panel, early observations (e.g., 2014–2015) naturally exhibit lower baseline scores due to secular economic growth and inflation. However, since absolute levels of capital and physical infrastructure dictate actual disaster recovery capacity, we deliberately retain this variance as a feature capturing real market growth rather than a temporal artifact.

The index design prioritizes interpretability. By retaining four principal components rather than collapsing them into a single score, we preserve the dominant national structure while acknowledging that we do not capture all variance. We also carefully assign directional signs to each component to ensure the orientation of the scale (i.e., which end is "up") is substantively meaningful. Since variance-based weighting inherently favors the market-scale dimension (PC1), high BRI values can reflect both scale and capacity; while county rankings remain stable across different weighting schemes (see Table 6), users should select the scheme that best aligns with their specific policy question.

Beyond weighting, the global standardization procedure introduces a deliberate temporal asymmetry. Since Market Scale (PC1) measures nominal economic growth, its effective contribution to the BRI score is inherently lower during early-panel event studies compared to later-panel studies. While this construction accurately reflects the lower absolute capitalization of historical markets, future iterations could employ quarter-by-quarter cross-sectional normalization to strictly isolate relative county rankings from macroeconomic inflation.

Finally, the event-study validation should be interpreted as a demonstration of behavioral alignment rather than a definitive model of causal identification. It relies on two state-quarter episodes where quarterly timing may shift effects across adjacent periods; furthermore, pre-treatment differences may persist after matching, and spatial spillovers across county lines can violate Stable Unit Treatment Value Assumptions (SUTVA). Future research can strengthen external validity by expanding the event set, estimating effects for additional outcome variables (e.g., number of establishments and payroll), and implementing designs that explicitly account for geographical proximity and spatial spillovers.

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