Resilient by Design: Isolating Impactful Climate Adaptation Measures in New England

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Abstract

As climate change impacts intensify and pose unprecedented threats to communities worldwide, the need for effective climate adaptation policies has never been greater. However, the effectiveness of these policies in reducing climate vulnerability remains poorly understood. This study examines the real-world effects of various climate policies on community vulnerability across New England. Using a comprehensive dataset of 1,232 policies from the Resilience and Adaptation in New England (RAINE) database and integrating Social Vulnerability Index (SVI) data, a blend of Staggered Treatment Difference-in-Differences (DID) models and Ordinary Least Squares (OLS) Fixed Effects regression models were used to evaluate the impact of policy features, types, and implementation levels. To address multicollinearity among predictors, sets of Principal Components (PCs) for climate policy components were included. The analysis reveals that policies focusing on infrastructure enhancements and regulatory measures are most effective in reducing vulnerability. In contrast, policies aimed at Social and Environmental Justice, Climate Mitigation, and Disaster Recovery may inadvertently increase vulnerability due to ineffective implementation, neglect of community needs, or negative externalities. Notably, local-level initiatives with state funding demonstrate significant success in enhancing resilience through increased resources. These findings provide insights into the practical effects of climate policies. For policymakers, the study highlights the need to prioritize infrastructure and regulatory measures to achieve reductions in vulnerability. It also underscores the potential pitfalls of poorly implemented policies in social justice, climate mitigation, and disaster recovery. By aligning policy goals with community-specific outcomes and leveraging state resources for local initiatives, this research offers a roadmap for crafting adaptive strategies that mitigate risks and bolster community resilience against climate change.

Keywords: Climate Policy, Climate Resilience, Vulnerability

Climate change is no longer a distant threat; its impacts are reaching all corners of the globe, including affluent countries [1, 2]. In such countries, communities are increasingly confronting severe climate-related challenges—frequent floods, rising sea levels, and extreme weather events are particularly impacting economically disadvantaged areas, given the major levels of inequality within some wealthy nations. This reality highlights that climate vulnerability is not confined to low-income or developing regions; it extends to vulnerable communities within wealthy countries as well [3, 4].

In this context, decreasing vulnerability is of vital importance. It is not merely about bouncing back from adverse events but about developing the capacity to adapt to and mitigate these impacts, thus reducing overall vulnerability. Understanding which climate policies effectively enhance resilience is crucial. This study aims to identify which types of policies are most successful in decreasing vulnerability, ensuring that resilience strategies are both impactful and equitable across diverse communities.

In response to the escalating effects of climate change, many communities are adopting various climate adaptation laws aimed at mitigating risks and enhancing resilience [5]. However, the effectiveness of these policies can vary significantly [6]. This study highlights that while some policies are widely implemented, their impact on increasing climate resilience is not uniform. Understanding which types of policies are most effective is essential for guiding future legislation and maximizing the benefits of climate adaptation efforts.

This paper seeks to address a fundamental question: Which types of climate policies are most effective in increasing resilience to climate change? To answer this, this work addresses the "how," "who," and "what" of climate policies:

- How do different features and types of climate policies influence resilience?
- Who—in terms of implementation jurisdiction—plays a role in successfully reducing vulnerability?
- What specific climate goals or focuses appear to be most effective?

To illustrate the current landscape of climate resilience, Figure 1 displays resilience levels across New England. This map reveals significant variations in resilience across the region, underscoring the necessity of effective and targeted climate policies. By analyzing these variations, this work aims to uncover which policy characteristics contribute most to reducing vulnerability and enhancing resilience.

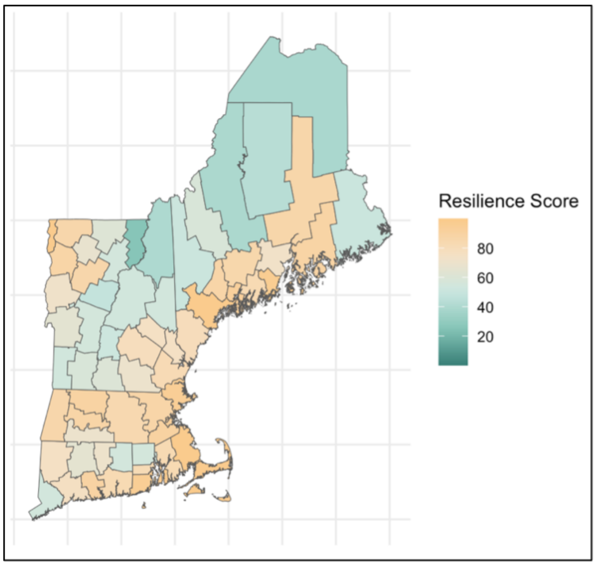

Fig. 1 Resilience Scores in New England States by County

Note: The mapped data displays resilience scores across New England, sourced from the Hazards Vulnerability & Resilience Institute's (HVRI) Baseline Resilience Indicators for Communities (BRIC) index. This index evaluates community resilience by considering six broad categories: social, economic, community capital, institutional, infrastructural, and environmental, providing a comprehensive assessment of resilience to natural hazards.

The primary objective of this paper is to analyze how various climate policies, including their features, types, levels of implementation, and focuses, influence the reduction of vulnerability across New England. Based on these insights, actionable recommendations are provided to guide policymakers in developing more effective climate adaptation strategies and enhancing community resilience against climate change.

1 Results

To assess how different climate policies influence vulnerability reduction, a series of Ordinary Least Squares (OLS) Fixed Effects regression models are employed.These models analyze the impact of policy features, types, levels of implementation, and goals on decreasing vulnerability (detailed model specifications are available in the Online Methods, Section 3.2.2).

This analysis draws on the Resilience and Adaptation in New England (RAINE) database, which includes data on 1,232 policies and plans from Massachusetts, New Hampshire, Maine, Connecticut, Rhode Island, and Vermont, spanning from 2000 to 2023 [7]. Additionally, the Social Vulnerability Index (SVI) from the CDC and ATSDR is integrated, providing county-level data on factors affecting vulnerability for the years 2000, 2010, 2014, 2016, 2018, 2020, and 2022 [8]. This combined dataset creates a panel of 476 county-year observations, allowing for the evaluation of the effectiveness of climate policies in reducing vulnerability across New England.

1.1 How Effective Are Different Policies? Dissecting the Features and Types that Shape Vulnerability

To understand how various policy features affect vulnerability levels, the top five most frequent policy features are analyzed: Economic Resilience, Ecosystem and Natural Resources, Government Bylaws and Ordinances, Infrastructure Built, and Social and Environmental Justice. The findings indicate that policies incorporating Government Bylaws and Ordinances and Infrastructure Built are associated with a decline in vulnerability levels (see Figure 2).

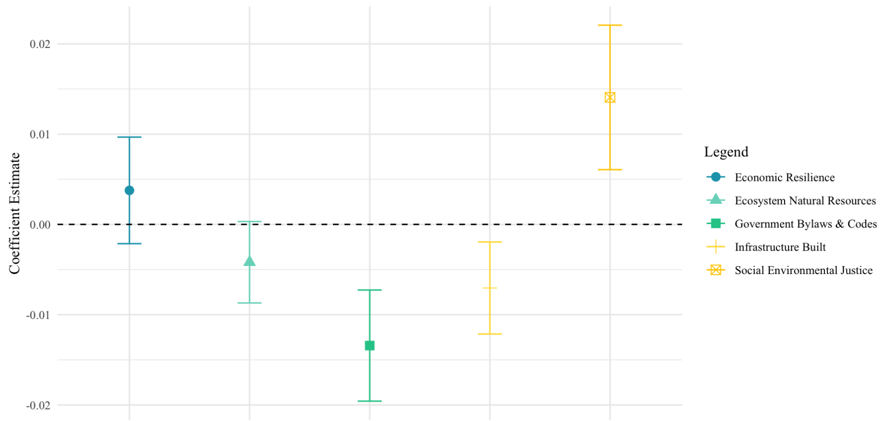

Fig. 2 The Impact of Policy Features on Climate Vulnerability

Note: The coefficient plot illustrates the results of the "Feature" models. It combines data from the Resilience and Adaptation in New England (RAINE) database, which details the stock of climate policy features for each county-year, and the CDC/ATSDR Social Vulnerability Index (SVI), which measures vulnerability levels in the same communities. In this plot, negative coefficients indicate a reduction in vulnerability to climate hazards (see Appendix A for corresponding Table).

Conversely, the inclusion of Economic Resilience in policies did not show a statistically significant impact on vulnerability reduction. Unexpectedly, policies featuring Social and Environmental Justice were associated with an increase in vulnerability [9]. This suggests that while policies aimed at promoting justice are well-intentioned, current implementation may not effectively address or mitigate vulnerabilities as intended.

The observed results highlight several intriguing dynamics in how different policy features impact vulnerability. Policies that focus on Government Bylaws and Ordinances, and Infrastructure Built tend to effectively reduce vulnerability. This outcome is likely because these features address fundamental aspects of climate adaptation—such as enhancing natural defenses, creating robust legal frameworks, and improving infrastructure resilience—that directly contribute to a community's ability to withstand climate impacts [4, 10–13].

The increase in vulnerability linked to Social and Environmental Justice policies could result from inadequate implementation or resources, indicating that these policies, despite their equity focus, may not yet be effectively translating into tangible resilience improvements [14, 15]. Alternatively, the challenges faced by vulnerable communities may be so complex that policies focusing solely on justice without comprehensive support may inadvertently fail to reduce vulnerability.

The analysis of different plan types—Adaptation Plans, Case Study Implementations, Climate Mitigation Documents, Disaster Recovery Plans, and Resilience Plans—reveals varying effects on vulnerability, as illustrated in Figure 3. For Adaptation Plans and Resilience Plans, the results indicate no statistically meaningful relationship with vulnerability.

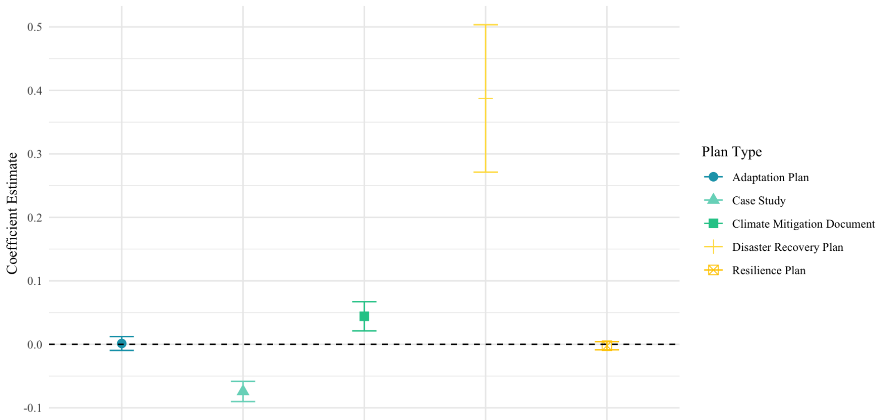

Fig. 3 The Impact of Plan Types on Climate Vulnerability

Note: The coefficient plot illustrates the results of the "Plan Type" models. It combines data from the Resilience and Adaptation in New England (RAINE) database, which details the stock of climate policy and plan types for each county-year, and the CDC/ATSDR Social Vulnerability Index (SVI), which measures vulnerability levels in the same communities. In this plot, negative coefficients indicate a reduction in vulnerability to climate hazards (see Appendix B for corresponding Table).

Climate Mitigation Documents show an increase in vulnerability. This may occur because these documents often prioritize reducing greenhouse gas emissions on a broad scale, which can overlook the immediate needs of the most vulnerable communities. Similarly, Disaster Recovery Plans are found to increase vulnerability, as alluded to in previous literature [16]. These plans focus primarily on managing the aftermath of disasters rather than preventing them or addressing underlying vulnerabilities. This approach might effectively 'pocket' funds for future recovery needs, potentially neglecting immediate risks and inadvertently leaving communities more exposed to subsequent events.

Case Study Implementation plans are the only plan type associated with a decrease in vulnerability. This effectiveness stems from their context-specific approach. By leveraging community needs and subsequently tailored solutions, these plans address the unique needs of local populations. The practical, evidence-based interventions provided by case studies are better suited to mitigate specific vulnerabilities and offer targeted strategies that directly improve resilience [17]. This localized focus ensures that the solutions are relevant and actionable, making them particularly effective in reducing vulnerability.

In summary, the "how" of decreasing vulnerability effectively includes a focus on infrastructure improvements, using case study-level context for plan implementation, and incorporating strategies into government bylaws and ordinances. These targeted approaches appear to build resilience by addressing immediate needs and embedding adaptive measures into local regulations.

1.2 Who's Making a Difference? The Role of Implementation Levels in Reducing Vulnerability

The analysis of implementation levels—State, Organization, Town, and Tribe—reveals varying impacts on vulnerability reduction, as illustrated in Figure 4. The results indicate that no level of implementation, except for the tribal level, is particularly effective in decreasing climate vulnerability.

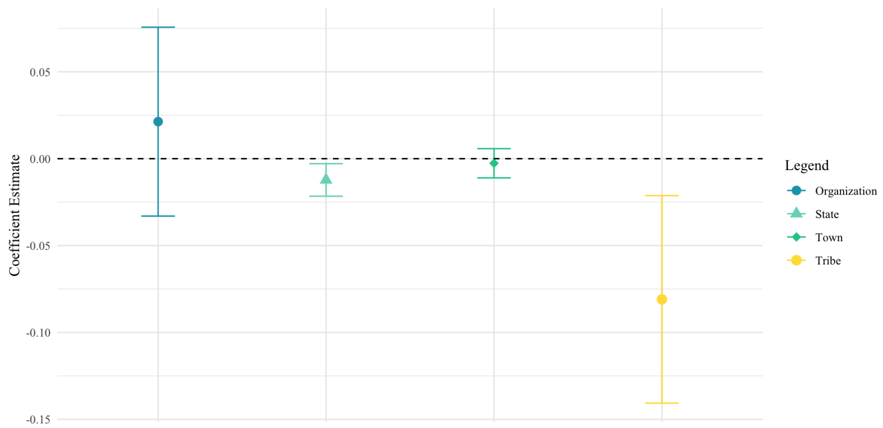

Fig. 4 The Impact of Implementation Level on Climate Vulnerability

Note: The coefficient plot illustrates the results of the "Implementation Level" models. It combines data from the Resilience and Adaptation in New England (RAINE) database, which details the stock of climate policy implementation in each implementation group for each county-year, and the CDC/ATSDR Social Vulnerability Index (SVI), which measures vulnerability levels in the same communities. In this plot, negative coefficients indicate a reduction in vulnerability to climate hazards (see Appendix C for corresponding Table).

Plans implemented by Indigenous Tribes are particularly effective in reducing vulnerability. This success may be due to Tribes' deep, place-based knowledge and their integration of traditional practices into adaptation strategies [18]. Additionally, external support for tribal initiatives often recognizes the high vulnerability of these communities and provides targeted, context-specific assistance, enhancing the effectiveness of their resilience measures [19]. State-level policy implementation is also shown to reduce vulnerability. This effect may be attributed to the ability of states to allocate funds to otherwise under-resourced countries that are particularly vulnerable, enabling governments to address specific issues more effectively [20, 21].

1.3 What Climate Goals Deliver? Assessing Effectiveness in Vulnerability Reduction

The analysis of policy focuses—Extreme Heat, Flooding, Saltwater Intrusion, Sea Level Rise, and Storm Surge—reveals important trends in vulnerability reduction, as depicted in Figure 5.

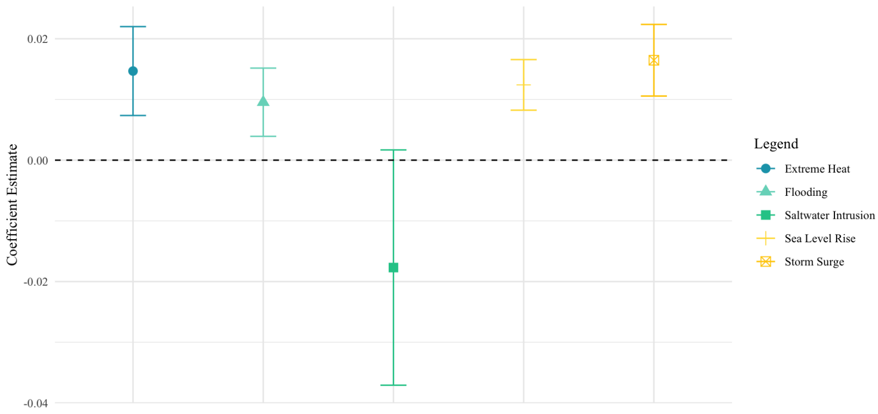

Fig. 5 The Effect of the Climate Goal on Vulnerability

Note: The coefficient plot illustrates the results of the "Goals" models. It combines data from the Resilience and Adaptation in New England (RAINE) database, which details the stock of climate policy goals and focuses for each county-year, and the CDC/ATSDR Social Vulnerability Index (SVI), which measures vulnerability levels in the same communities. In this plot, negative coefficients indicate a reduction in vulnerability to climate hazards (see Appendix D for corresponding Table).

Policies aimed at Flooding, Extreme Heat, Sea Level Rise, and Storm Surge are associated with an increase in vulnerability. This may be because these policies often do not prioritize enhancing community-level resilience. Instead, they might focus on broader or less targeted interventions, potentially neglecting the specific needs of vulnerable local populations [22].

More specifically, policies aimed at flooding, extreme heat, sea level rise, and storm surge often prioritize coastal areas, which can lead to uneven resilience efforts across the state. For instance, as shown in Figure 1, counties along the Appalachians exhibit systematically higher vulnerability, yet these regions are frequently overlooked in climate discussions. The "Blue Ridge and Northern Highlands" area is one of the most drought-prone [23] regions of the country, and, when it does rain, suffers from flooding [24, 25] exacerbated by coal mining practices and warming temperatures. These environmental changes are also damaging local forests, water quality [26], and increasing wildfire risks.

This coastal-centric focus not only neglects the serious vulnerabilities faced by rural and less developed areas but may also widen the inequality divide as resources are disproportionately allocated to wealthier coastal regions.This highlights a gap in climate policies: to be more effective, they should incorporate comprehensive strategies that address community-specific vulnerabilities, ensuring that resilience measures are integrated into the broader climate adaptation framework. Climate policies must adopt a more holistic approach that considers the unique vulnerabilities of all regions, thereby enhancing community-level resilience and ensuring equitable, targeted interventions for all affected populations.

In all, the findings reveal that effective climate policies focus on enhancing infrastructure, incorporating case study-level context, and prioritizing governance. By understanding the various features of policies, types of plans, implementation levels, and goals, we can better evaluate their effectiveness in reducing climate vulnerability. Future policy initiatives should prioritize case-specific, evidence-based approaches that directly address the needs of vulnerable communities to ensure resilience against climate change.

1.4 The Success Story of Essex, MA: How Comprehensive Policy Transformed Climate Resilience

The "Saving the Great Marsh" project exemplifies an effective climate adaptation policy by integrating key elements such as bylaws and ordinances, infrastructure building, local-level implementation, and a case study approach. Focused on restoring the resilience of the Great Marsh in Essex County, Massachusetts, the project incorporates innovative ditch remediation techniques to address the ecosystem's vulnerabilities [27]. A significant factor contributing to the project's success is its robust funding at the state level, including grants from the National Coastal Resilience Fund and the MassBays grant. This financial support not only facilitates restoration efforts but also generates substantial employment opportunities, helping to alleviate socioeconomic vulnerabilities and adding an important layer to the project's comprehensive approach. Figure 6 displays the resilience map of Massachusetts, highlighting Essex County as a region with high resilience levels.

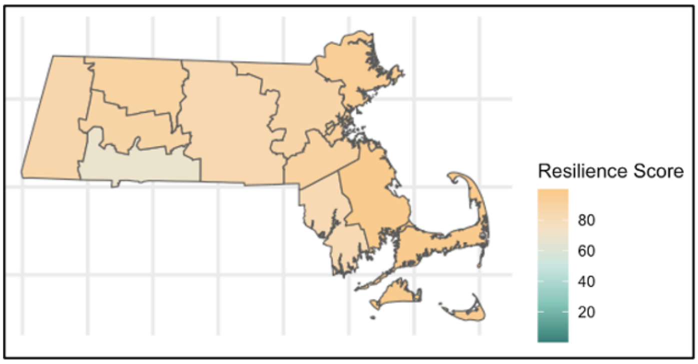

Fig. 6 Levels of Climate Resilience in Massachusetts

Note: The mapped data displays resilience scores across New England, sourced from the Hazards Vulnerability & Resilience Institute's (HVRI) Baseline Resilience Indicators for Communities (BRIC) index. This index evaluates community resilience by considering six broad categories: social, economic, community capital, institutional, infrastructural, and environmental, providing a comprehensive assessment of resilience to natural hazards. This increased resilience in Essex is partly attributable to successful projects like the Great Marsh restoration, which combine targeted regulatory measures, local expertise, and infrastructure improvements. By addressing both environmental and socioeconomic factors, this project demonstrates how integrated climate policies can effectively enhance community resilience and reduce vulnerability.

2 Discussion

The analysis reveals significant insights into how various climate policies impact climate vulnerability and resilience. Policies that focus on Government Bylaws and Ordinances, and Infrastructure Built are associated with a notable decline in vulnerability. This suggests that policies incorporating these elements address core aspects of climate adaptation by enhancing natural defenses, establishing robust legal frameworks, and upgrading infrastructure. Additionally, Case Study Implementation Plans prove effective due to their context-specific approaches, which allow for tailored solutions that directly address local needs. The analysis also shows that Indigenous Tribes' plans were particularly successful, providing support that localized efforts have an impact on vulnerability reduction. It also shows that when climate policies target various outcomes and goals, they should be mindful of the impact on community vulnerability.

This study faces several limitations. Firstly, data constraints hindered the availability of annual vulnerability scores at a granular level, impacting the temporal precision of the analysis. Furthermore, while this study provides valuable insights into policy effectiveness, it does not establish causal relationships. The observed trends offer a starting point for understanding policy impacts but do not delve into the underlying mechanisms or causal factors.

This paper advances the field of climate policy by clarifying which specific aspects of climate policy are most effective in reducing overall community vulnerability. While existing research often focuses on policy goals, this study examines how these policies impact vulnerability in practice. Policymakers should prioritize policies that not only aim to achieve their stated objectives but also effectively enhance resilience. The findings underscore the need for more contextualized policies that address vulnerabilities without causing unintended negative consequences. By focusing on the practical effects of climate policies on community vulnerability, this research fills a crucial gap in understanding, ensuring that policies do not inadvertently increase vulnerability while pursuing climate goals.

Future research should explore the causal mechanisms behind the observed trends to better understand how different policies influence vulnerability. Furthermore, investigating the specific implementation practices and challenges of Social and Environmental Justice policies could reveal why these may not be reducing vulnerability as intended. Additionally, examining the role of community engagement and traditional knowledge in enhancing policy effectiveness would provide deeper insights into localized adaptation strategies. Finally, more granular longitudinal studies that track policy impacts over time and across diverse contexts can further refine our understanding of how to design and implement effective climate resilience measures.

3 Online Methods

This section provides a comprehensive overview of the data and methodology used in the analysis as well as additional robustness checks. It outlines the data, control variables, principal components, and statistical techniques employed to evaluate the impact of various facets of climate policies on community vulnerability. Specifically, the dataset consists of 1,232 policies from the Resilience and Adaptation in New England (RAINE) database and integrates Social Vulnerability Index (SVI) data, census data, and climate exposure data. First, the Data and Model Specification are discussed. Then, insights on robustness are provided using Principal Component Analysis (PCA) to address multicollinearity, Fixed and Random Effects regression models, Hausman tests, Granger causality tests, and difference-in-differences (DID) analyses.

3.1 Data

The dataset in this analysis consists of 1,232 policies from the Resilience and Adaptation in New England (RAINE) database. By integrating Social Vulnerability Index (SVI) data, census data, and climate exposure data, Ordinary Least Squares (OLS) Fixed Effects regression models are applied to evaluate the impact of policy features, types, and implementation levels [7, 8, 28, 29]. To handle multi-collinearity issues among predictors, sets of Principal Components (PCs) for various climate policy components are included.

3.1.1 Socio-economic Variables

The socio-economic control variables are derived from the `tidycensus` data and encompass various social and demographic factors [30]. These factors align with the Morelli et al. [31] climate adaptation screening focus areas in being known to influence community vulnerability. They are also inherently related to the potential effectiveness of climate adaptation policies. These control variables include:

- Below 150% Poverty Rate (% of population)

- Unemployment Rate (% of population)
- Housing Cost Burden (% of population)
- Minority Household Rate (% of population)
- Single Parent Household Rate (% of population)
- Mobile Home Housing Rate (% of population)
- English Second Language (ESL) Rate (% of population)

3.1.2 Baseline Climate Exposure

The variable that baseline climate exposure is derived from the Climate Risk Index [29]. This inclusion enables the analysis to account for the inherent vulnerability of communities to climate-related risks, thereby enhancing the robustness of the findings.

3.1.3 Policy Control Variables

To address potential multicollinearity among climate policy variables, Principal Component Analysis (PCA) is employed. PCA reduces the dimensionality of the data by creating a new set of uncorrelated variables, known as principal components, that capture the maximum variance in the original data [32, 33].

Specifically, sets of principal components derived from the "Feature," "Plan Type," and "Goal" categories are controlled for (see Figures 7, 8, and 9 respectively for the Principal Component breakdown for model inclusion).

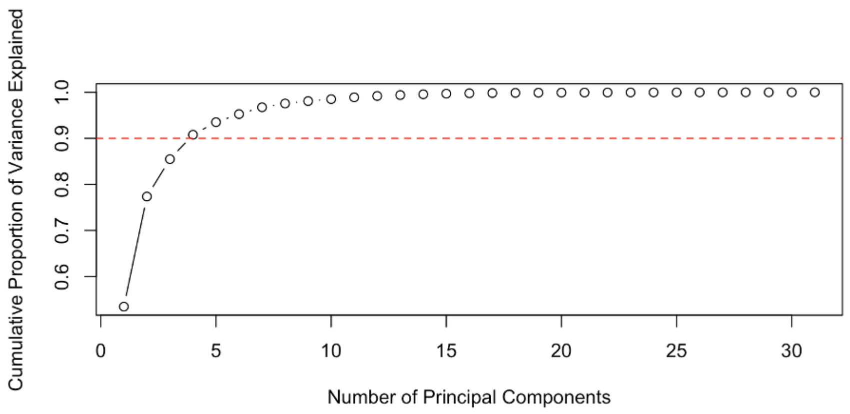

Fig. 7 "Feature" Principal Component Analysis
Note: The first four principal components of "Feature" are observed to explain the necessary variation in the main models, so these components are included in the analysis.

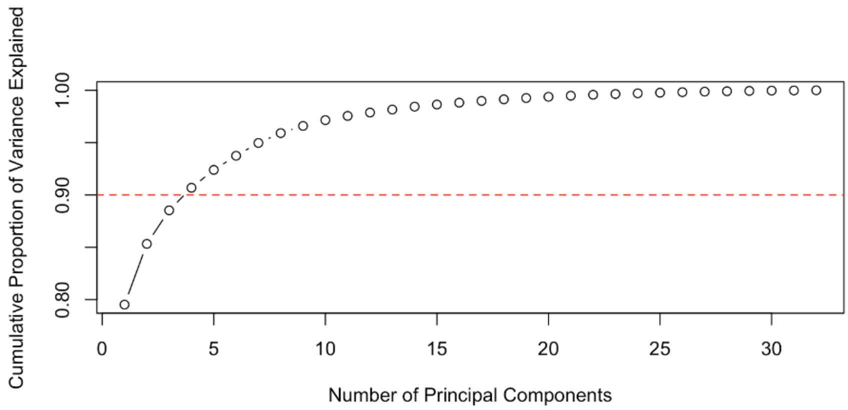

Fig. 8 "Plan Type" Principal Component Analysis
Note: The first three principal components of "Plan Type" are observed to explain the necessary variation in the main models, so these components are included in the analysis.

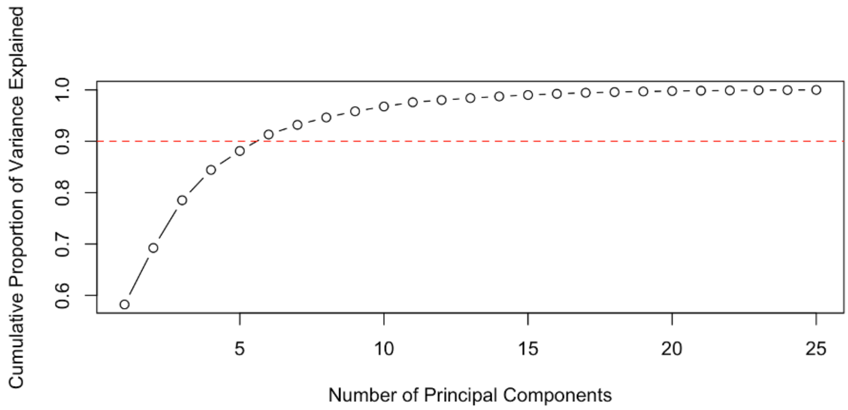

Fig. 9 "Goals" Principal Component Analysis
Note: The first five principal components of "Goals" are observed to explain the necessary variation in the main models, so these components are included in the analysis.

For the purposes of this analysis, this approach allows for the inclusion of policy-relevant information without introducing unnecessary collinearity in the model. Mathematically, PCA involves the following steps outlined in Equations 1–4:

1. **Centering the Data:**

$$X_c = X - \bar{X} \tag{1}$$

where X is the original data matrix and $\bar{X}$ is the mean of each variable.

2. **Covariance Matrix:**

$$C = \frac{1}{n-1} X_c^T X_c \tag{2}$$

where C is the covariance matrix and n is the number of observations.

3. **Eigenvalue Problem:** To find the principal components, the eigenvalue problem is solved:

$$C\mathbf{v} = \lambda\mathbf{v} \tag{3}$$

where λ are the eigenvalues and $\mathbf{v}$ are the corresponding eigenvectors.

4. **Principal Components:** The principal components Z can be computed as:

$$Z = X_c\mathbf{V} \tag{4}$$

where $\mathbf{V}$ is the matrix of eigenvectors corresponding to the largest eigenvalues.

This technique effectively mitigates the biasing effects of multicollinearity, which arises when predictor variables exhibit high correlation, ultimately resulting in unreliable coefficient estimates. Having delineated the data, the next step is model specification.

3.2 Model Specification

This section outlines the model specification and validation process. It discusses the assumptions of linearity and heteroskedasticity, and compares fixed effects and random effects models. The Hausman test is conducted to determine the most appropriate model for the analysis.

3.2.1 Linearity

Several methods are employed to ensure the robustness of the results. First, the linearity of the relationships between the independent variables and the dependent variable is assessed using scatter plots and residual plots (see Figure 10). Linearity is a key assumption of regression analysis, and ensuring its validity strengthens the interpretability of the model's results. Residual plots are examined to identify any patterns or outliers that might indicate violations of model assumptions.

While the linearity appears to be satisfactory, clustered standard errors based on Huber-White adjustments are employed across all models to account for potential heteroskedasticity [34, 35].

Furthermore, skewness and kurtosis for the independent variables were checked to assess their distributions and determine which variables to log transform. The variables *Single Parent*, *Unemployment*, *Housing Burden*, *Poverty*, *Minority*, *Mobile Homes*, *ESL*, and *Climate Exposure* were identified and logged to address concerns related to skewness and non-linearity. The logged versions of these variables were included in all models.

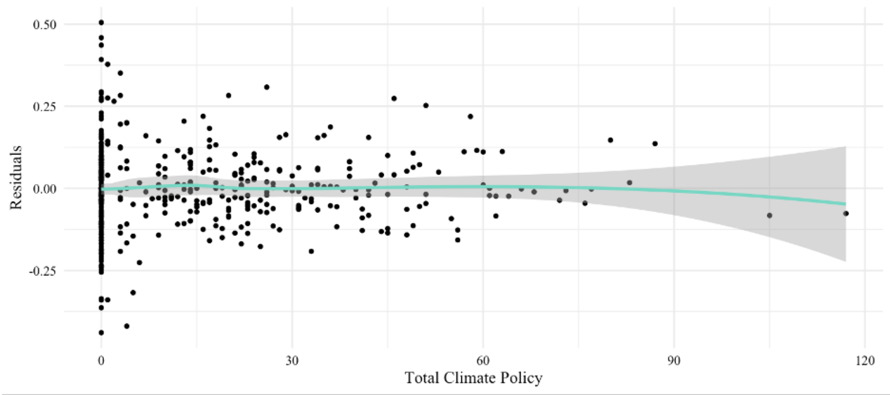

Fig. 10 Total Policy on Vulnerability

3.2.2 Model Fit

Given that the data is linear and in panel format, a determination is made regarding whether a random effects or fixed effects model is more suitable. The fixed effects model is shown in Equation 5:

$$\text{ClimateVulnerability}it = \beta_0 + \beta_1 \text{PolicyComponent}_{it} + \beta_{\text{Controls}} + v_i + \epsilon_{it} \quad (5)$$

where *ClimateVulnerabilityit* denotes the dependent variable for individual i at time t, while *PolicyComponentit* encapsulates the feature, plan type, implementation level, or goal of the policy (alternatively referenced as *FEATUREit*, PLANit, IMPLEMENTATIONit, or GOALit). Specifically, *FEATUREit* signifies the policy feature variable (Economic Resilience, Ecosystem and Natural Resources, Government Bylaws and Ordinances, Infrastructure Built, or Social and Environmental Justice), while *PLANit* indicates the plan type variable (Adaptation Plans, Case Study Implementations, Climate Mitigation Documents, Disaster Recovery Plans, and Resilience Plans). Moreover, *IMPLEMENTATIONit* refers to the variable representing the level of implementation (Organization, State, Town, or Tribe), and *GOALit* is the policy goal variable (Extreme Heat, Flooding, Saltwater Intrusion, Sea Level Rise, or Storm Surge). In this context, β_0 represents the intercept, β_1 is the coefficient associated with the feature variable, β_{Controls} signifies the composite index of control variables, u_i denotes the individual-specific effect (fixed effect), and ϵ_{it} is the idiosyncratic error term.

The random effects model is specified in Equation 6:

$$\text{ClimateVulnerability} = \beta_0 + \beta_1 \text{PolicyComponent}_i + \beta_{\text{Controls}} + u_i + \epsilon_{it} \quad (6)$$

In contrast to the fixed effects model, which accounts for individual-specific effects (u_i) that are assumed to be correlated with the independent variables, the random effects model incorporates a term (v_i) that captures individual-specific variations while assuming these variations are uncorrelated with the explanatory variables. This assumption allows for the inclusion of time-invariant variables in the analysis. A Hausman test is conducted to evaluate the relative appropriateness of these models. Equation 7 represents the Hausman test:

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'[\mathrm{Var}(\hat{\beta}_{FE}) - \mathrm{Var}(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \tag{7}$$

where $\hat{\beta}_{FE}$ indicates the coefficients estimated by the Fixed Effects Model, and $\hat{\beta}_{RE}$ signifies the coefficients estimated by the Random Effects Model. The variance of the coefficients from the Fixed Effects Model is denoted by $\mathrm{Var}(\hat{\beta}_{FE})$, while $\mathrm{Var}(\hat{\beta}_{RE})$ represents the variance of the coefficients from the Random Effects Model. The results of the Hausman test are displayed in Table 3.2.2:

Table 1 Hausman Test Results

Statistic	Value
Test Statistic (chisq)	770.5
Degrees of Freedom (df)	21
p-value	¡ 2.2e-16
Alternative Hypothesis	One model is inconsistent

Note: As a sample, the Economic Resilience feature was used to estimate the Hausman test results from Equations 5 and 6.

The results of the Hausman test indicated a preference for the fixed effects model over the random effects model. Consequently, the fixed effects model is specified in the primary analysis. While the fixed effects model is estimated in the main text, it is noteworthy that the random effects models demonstrate robustness to the findings, as shown in Appendix E. Furthermore, the high-dimensional effects captured in the random effects models are well-suited to account for the hierarchically structured Baseline Climate Exposure.

A random effects model is employed to account for unobserved heterogeneity at the community level (see Equation 5). This approach is particularly suited to the study design, as it recognizes that communities may possess inherent characteristics that influence their vulnerability scores, beyond the variables included in the model [36]. By incorporating random effects, these variations are accounted for, leading to more accurate estimates of the true effects of climate policies on community vulnerability. where *ClimateVulnerability* is the dependent variable, and $PolicyComponent_i$ represents the feature, plan type, implementation level, or goal of the policy (otherwise referred to as $FEATURE_i$, PLAN_i, $\mathrm{IMPLEMENTATION}_i$, or GOAL_i). Specifically, $\mathrm{FEATURE}_i$ denotes the policy feature variable (Economic Resilience, Ecosystem and Natural Resources, Government Bylaws and Ordinances, Infrastructure Built, or Social and Environmental Justice), while PLAN_i indicates the plan type variable (Adaptation Plans, Case Study Implementations, Climate Mitigation Documents, Disaster Recovery Plans, and Resilience Plans). Furthermore, IMPLEMENTATION$_i$ refers to the level of implementation variable (Organization, State, Town, or Tribe), and GOAL$_i$ is the policy goal variable (Extreme Heat, Flooding, Saltwater Intrusion, Sea Level Rise, or Storm Surge). In this equation, β_0 represents the intercept, β_1 is the coefficient for the feature variable, β_{Controls} denotes the index of control variables, u_i is the individual-specific effect (random effect), and ϵ_{it} is the idiosyncratic error term.

Another reason the random effects model is optimal is that the climate exposure control variable is only available at the spatial level, not the temporal level. This is because it represents aggregate climate stress across a region, not changing over time and comes from the CRSI index [37]. The random effects model can effectively account for this spatial variation in climate exposure.

3.3 Robustness

This section provides a detailed overview of the robustness checks conducted to ensure the validity of the results. It discusses the use of Principal Component Analysis (PCA) to address multicollinearity, Granger causality tests to establish temporal relationships, and difference-in-differences (DID) analysis to assess the causal impact of climate policies.

3.3.1 Multicollinearity

The concept and measurement of climate vulnerability inherently encompass various socio-demographic factors and climate variables. To ensure that the models are robust against any unnecessary multicollinearity, Principal Component Analysis (PCA) is employed (see Equations 1–4) on all climate vulnerability (CV) socio-demographic factors and climate variables. The results of this analysis are presented in Figure 11, illustrating the correlations among the principal components.

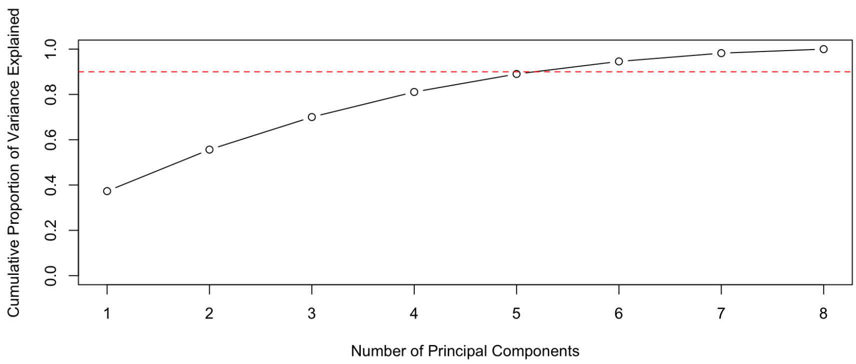

Fig. 11 Principal Component Analysis of Socio-Economic & Climate Control Variables
Note: The first seven principal components explain the necessary variation in the models.

Furthermore, Figure 12 depicts how these principal components correlate with the outcome variable. Notably, Principal Component 1 (PC1) exhibits a high correlation, prompting its exclusion from the model. Instead, the analysis utilizes Principal Components 2 through 7 as predictors. This approach ensures that the outcome variation is not unnecessarily influenced by certain predictors.

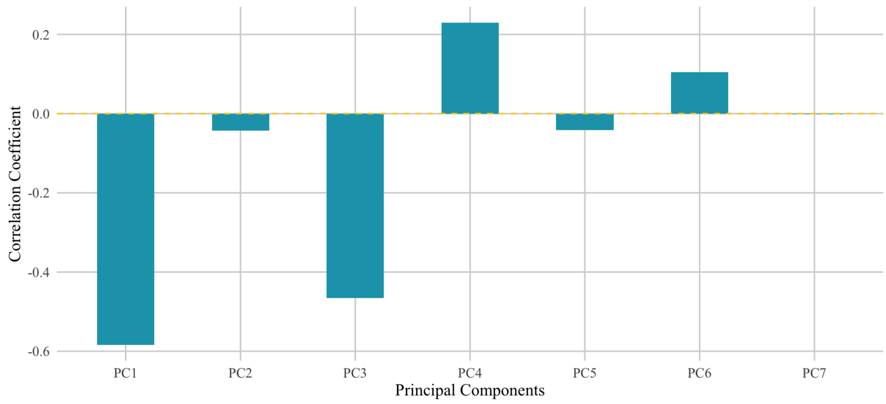

Fig. 12 Principal Component Analysis Correlation with Dependent Variable

The results remain robust and comparable to those obtained from the main models, as shown in Figure 13 and Table F9 in Appendix F. The only difference is that in these models, the State level of implementation shifts to statistically significant at the .1 level.

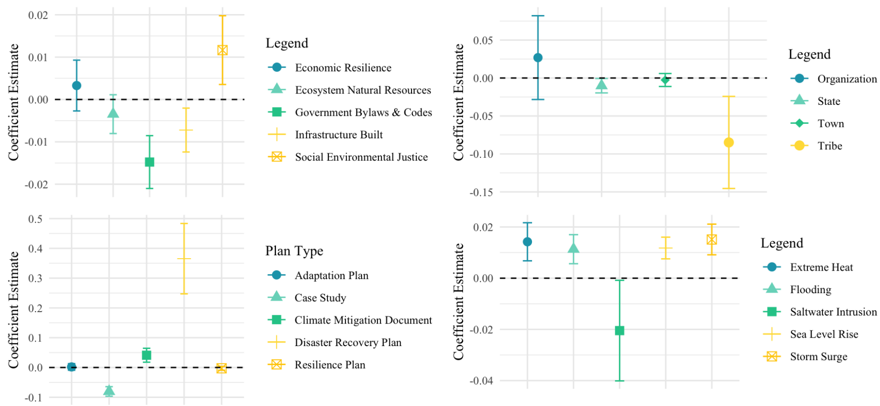

Fig. 13 Main Models (Figures 2-5) with PC 2-7 Controls

Furthermore, Figure 14 shows the simple bivariate fixed effects model outcomes only including the policy-related principal controls to ensure the isolated effect of the policies (see corresponding output in Appendix G).

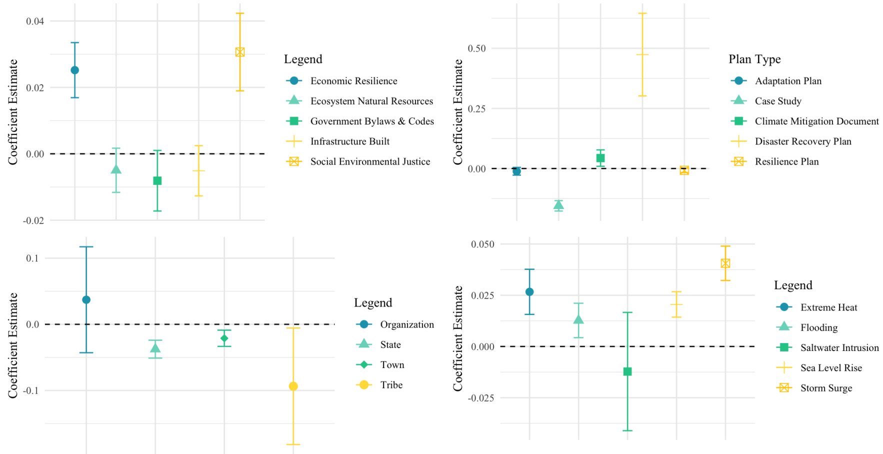

Fig. 14 Bivariate Models corresponding with main models in Figures 2-5

These models are also robust, with some small changes. The Town-level of implementation now leads to lower climate vulnerability, leaving only the Organizational level as ineffective. Additionally, differences are observed in the policy features, with Government Bylaws and Ordinances, and Infrastructure Built slightly shifting to significance only at the 0.1 level.

3.3.2 Causality

Additionally, looped Granger causality tests are conducted to explore the temporal relationships between climate policies (indicated here by Total Climate Policies in a given county-year) and SVI scores. Granger causality is a statistical technique used to assess whether one time series variable can predict another (see Equation 8). In this context, the test assists in determining whether the implementation of climate policies precedes any measurable changes in community vulnerability scores [38].

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} + \epsilon_t \tag{8}$$

where Y_t signifies the *climate readiness score*, which is the dependent variable being forecasted, and X_t stands for the *adaptation laws*, the independent variable under examination for Granger causality. The symbols p and q represent the number of lags for Y and X, respectively. The constant term is denoted by α, with β_i and θ_j representing the coefficients for the lagged variables. Lastly, ϵ_t indicates the error term in the model.

The results of the Granger causality test (see Table 2) show statistical significance, indicating a causal relationship between climate adaptation policies and reduced vulnerability (p ¡ 0.05).

Furthermore, to capture the effect of climate policy emergence on vulnerability, Callaway and Sant'Anna's [39] doubly robust staggered treatment methodology is

Table 2 Granger Causality Test

Statistic	Value
F-Test	25.748
Degrees of Freedom (df1, df2)	2, 938
p-value	1.30E-11

Note: The test assesses whether total policy influences vulnerability through Granger causality. Null Hypothesis: Total Policy does not Granger-cause Vulnerability.

leveraged as a robustness check. Formally, the model is represented by Equation 9, where Y represents climate vulnerability:

$$Y = \beta_0 + \beta_1 \text{Policy} + \beta_2 \text{Established} + \beta_3(\text{Policy} \times \text{Established}) + \epsilon \tag{9}$$

where *Policy* indicates the emergence of a climate policy in the county, *Established* represents the year in which the policy was established, and ϵ denotes the error term. Because of the nature of the staggered treatment, the temporal component of when the policy was *Established* is interacted with policy location.

While limited in the data availability of pretreatment periods, this approach strengthens the causal inference by addressing potential confounding variables and selection bias. The analysis reveals a statistically significant 18.5% reduction in vulnerability within the full post-treatment period (see Supplemental Information for table outputs). To visualize this decline over time, please refer to Figure 15, which presents the full event study plot. The plot depicts a steady downward trend in vulnerability following policy implementation, highlighting the potential effectiveness of climate adaptation policies in reducing community vulnerability.

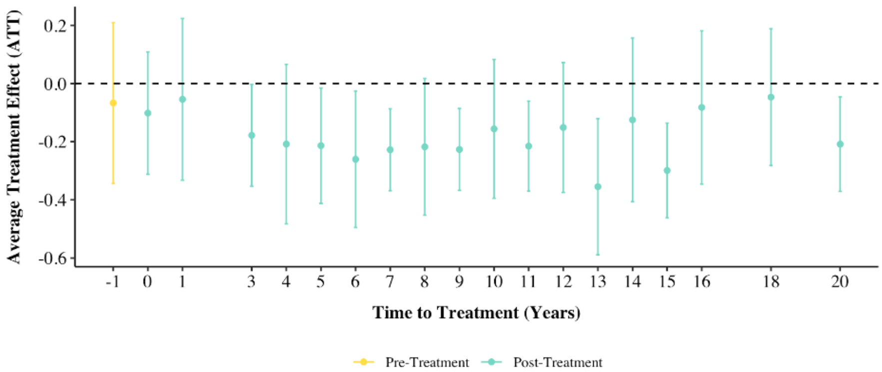

Fig. 15 DID Event Plot for Emergence of Climate Policy on Vulnerability

While not all aspects of climate policies could be analyzed using the difference-in-differences approach due to insufficient pre- or post-treatment periods, the results for those with adequate data are presented below (see Figures 16-20. The impact of resilience plans, social and environmental justice policies, infrastructure development, government laws and ordinances, and adaptation plans on climate vulnerability is evaluated, examining each element in turn.

First, resilience plans are observed to contribute to a gradual decline in vulnerability over time during the post-treatment period (see Figure 16). This effect becomes statistically significant approximately five years after implementation. Specifically, the pooled average treatment effect on the treated units in the full post-treatment period is -1.02, indicating a notable reduction in vulnerability attributable to resilience plans.

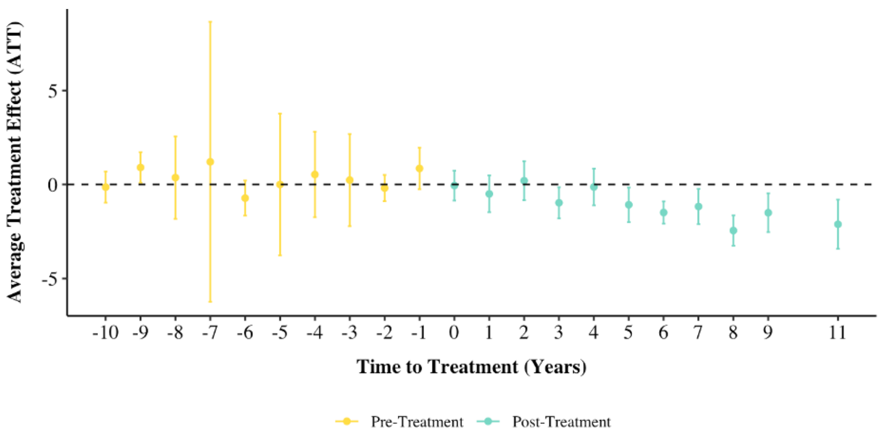

Fig. 16 DID Event Plot for Emergence of Resilience Plans on Vulnerability

Regarding the emergence of social and environmental justice policies, the full post-treatment period does not show statistical significance in terms of impact on vulnerability (see Figure 17). However, 12 years post-treatment, these policies become statistically significant, leading to an increase in vulnerability. During this period, the average treatment effect is 3.44, indicating a quite latent but notable rise in vulnerability.

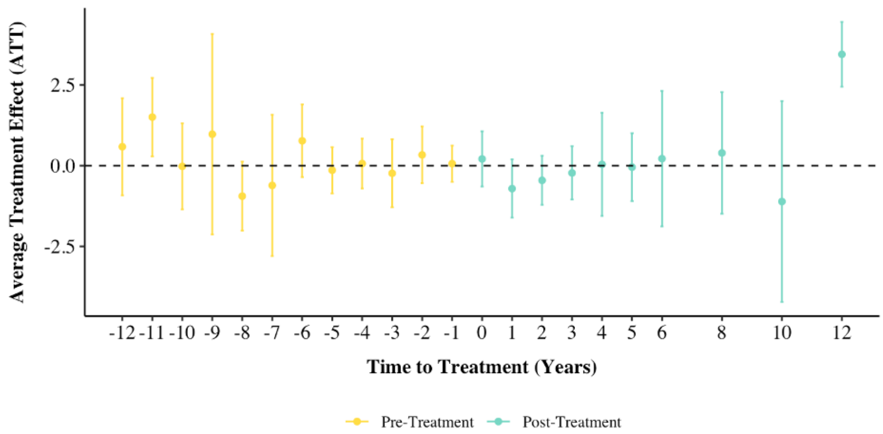

Fig. 17 DID Event Plot for Emergence of Social and Environmental Justice on Vulnerability

For the effect of infrastructure development on vulnerability, there is no statistical significance observed in the full post-treatment period (see Figure 18). However, a downward trend in vulnerability is noted, with a statistically significant effect emerging 11 years post-treatment. In this period, the average treatment effect is approximately -1.39.

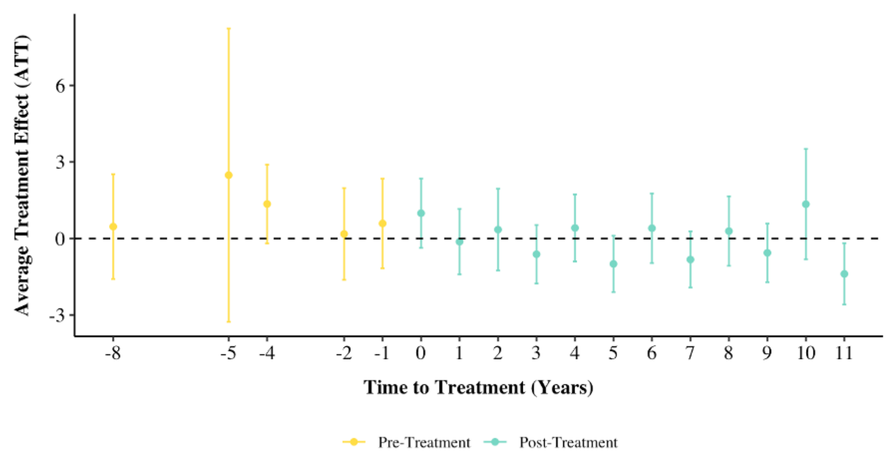

Fig. 18 DID Event Plot for Emergence of Infrastructure Built on Vulnerability

For government laws and ordinances, the analysis of the full pooled post-treatment period reveals an average treatment effect on the treated units of approximately -0.41, indicating a modest decrease in vulnerability (see Figure 19).

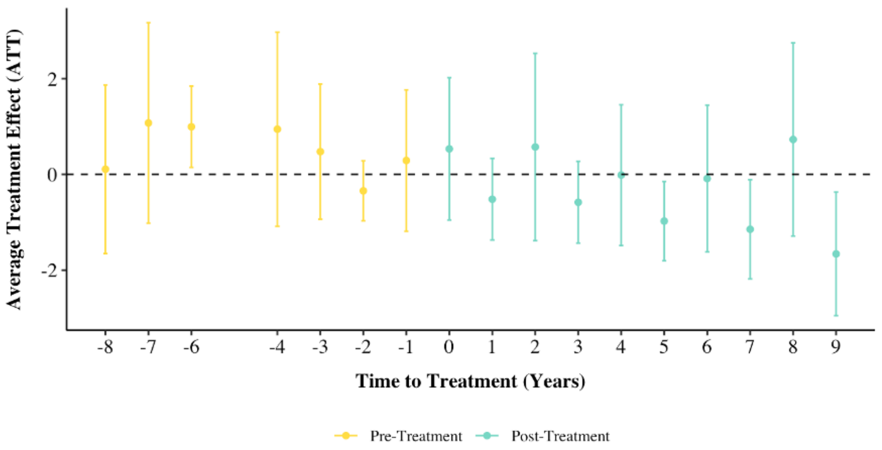

Fig. 19 DID Event Plot for Emergence of Government Laws and Ordinances on Vulnerability

Finally, in the full post-treatment period, adaptation plans demonstrate a significant impact on reducing vulnerability (see Figure 20). Specifically, these plans result in an average treatment effect of -1.24, reflecting a meaningful decline in vulnerability.

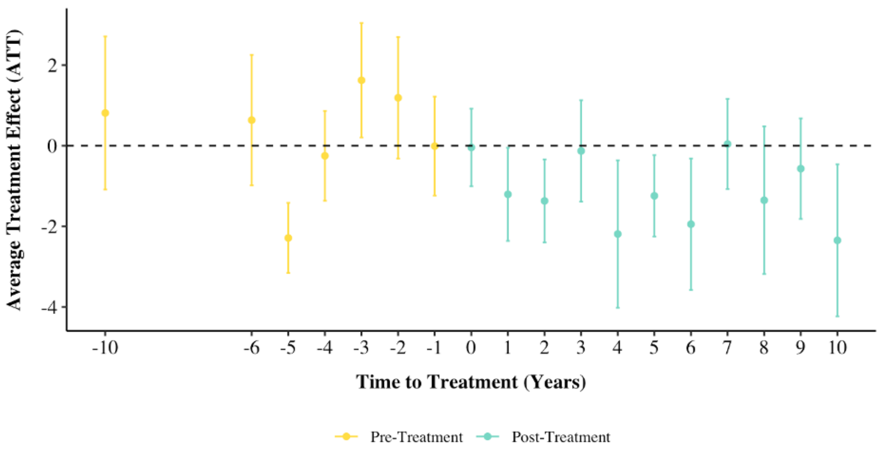

Fig. 20 DID Event Plot for Emergence of Adaptation Plan Type on Vulnerability

Overall, the robustness checks utilizing the difference-in-differences (DID) approach provide insights into the efficacy of the emergence of various climate policies on community vulnerability, rather than their cumulative effect as in the main text. The DID analysis reveals nuanced impacts of different climate policy types over time. Resilience plans show a significant reduction in vulnerability, becoming particularly meaningful approximately five years post-implementation, while social and environmental justice policies, though not immediately impactful, eventually lead to increased vulnerability after 12 years. Infrastructure development demonstrates a delayed but significant decrease in vulnerability 11 years post-treatment. Government laws and ordinances contribute to a modest reduction in vulnerability, while adaptation plans show a meaningful decline across the full post-treatment period. These findings collectively highlight the diverse temporal effects of climate policies, reinforcing the importance of considering both immediate and long-term impacts in evaluating policy effectiveness.

In conclusion, this study leverages a comprehensive methodological approach to assess the impact of climate adaptation policies on community vulnerability across New England. A fixed effects model with clustered standard errors is utilized to account for unobserved heterogeneity at the community level. Principal Component Analysis (PCA) is employed to address multicollinearity among climate policy variables. Control variables from the United States Census and American Social Survey and the Climate Resilience Screening Index (CRSI) are incorporated to account for factors influencing community characteristics and climate exposure. Furthermore, the linearity of the models is assessed, and Granger causality tests are employed to strengthen the causal inferences drawn from the analysis. By combining these techniques, this study provides a robust framework for evaluating the effectiveness of climate adaptation policies in reducing vulnerability across communities.

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Data availability. The data supporting this study are publicly available from several sources. The Climate Change - Resilience and Adaptation in New England (RAINE) database, which includes comprehensive climate policy data for New England, can be accessed at EPA's RAINE page. US Census data, including demographic and socioeconomic information, is available through the TidyCensus tool. The CDC/ATSDR Social Vulnerability Index (SVI) data, providing insights into community social vulnerabilities, can be downloaded from CDC's SVI page, with detailed documentation available at SVI Documentation. Additionally, data on climate exposure and risks is accessible via the EPA's Climate Exposure (CRSI) page. These resources provide the datasets used in the analysis and are openly available for public use and verification. The combined and cleaned data can be found in this GitHub Repository.

Code availability. Data analysis was conducted in R and can be found in this GitHub Repository.

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Appendix A Policy Feature Table Output

Table A1 shows the output of Figure 2.

Table A1 Policy Features

	Climate Vulnerability				
	(1)	(2)	(3)	(4)	(5)
Economic Resilience	0.004 (0.006)				
Ecosystem Natural Resources		−0.004 (0.005)			
Government Bylaws			−0.013** (0.006)		
Infrastructure Built				−0.007 (0.005)	
Social Environmental Justice					0.014* (0.008)
Poverty*	0.087*** (0.011)	0.087*** (0.011)	0.088*** (0.011)	0.088*** (0.011)	0.087*** (0.011)
Unemployment*	0.161*** (0.021)	0.162*** (0.020)	0.165*** (0.020)	0.161*** (0.020)	0.158*** (0.020)
Housing Burden*	−0.002 (0.009)	−0.002 (0.009)	−0.001 (0.009)	−0.001 (0.009)	−0.002 (0.009)
Minority*	−0.013** (0.006)	−0.012** (0.006)	−0.013** (0.006)	−0.012* (0.006)	−0.012* (0.006)
Single Parent Household*	−0.013 (0.014)	−0.014 (0.014)	−0.011 (0.014)	−0.012 (0.014)	−0.015 (0.014)
Mobile Homes*	0.071*** (0.012)	0.071*** (0.012)	0.069*** (0.012)	0.070*** (0.012)	0.072*** (0.012)
ESL*	0.019 (0.012)	0.019 (0.012)	0.019 (0.012)	0.019 (0.012)	0.019 (0.012)
Feature PC	No	No	No	No	No
Type PC	Yes	Yes	Yes	Yes	Yes
Goal PC	Yes	Yes	Yes	Yes	Yes
Implementation Level FEs	Yes	Yes	Yes	Yes	Yes
Observations	476	476	476	476	476
R^2	0.662	0.662	0.665	0.663	0.664
Adjusted R^2	0.585	0.585	0.589	0.586	0.587
F Statistic (df = 21; 387)	36.020***	36.084***	36.631***	36.230***	36.397***

Note: *Variable** indicates logged values; Significance levels are $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Appendix B Policy Type Table Output

Table B2 shows the output of Figure 3.

Table B2 Plan Types

	Climate Vulnerability				
	(1)	(2)	(3)	(4)	(5)
Adaptation Plan	0.001				
	(0.011)				
Case Study		−0.074***			
		(0.016)			
Mitigation Document			0.044*		
			(0.023)		
Disaster Recovery Plan				0.387***	
				(0.116)	
Resilience Plan					−0.002
					(0.006)
Poverty*	0.088***	0.084***	0.087***	0.085***	0.087***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
Unemployment*	0.161***	0.152***	0.161***	0.163***	0.161***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Housing Burden*	−0.001	−0.0002	−0.002	−0.003	−0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Minority*	−0.012*	−0.014**	−0.011*	−0.011*	−0.012*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Single-Parent Household*	−0.014	−0.010	−0.014	−0.015	−0.014
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mobile Homes*	0.071***	0.067***	0.072***	0.073***	0.071***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ESL*	0.019	0.009	0.019	0.020*	0.019*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Feature PC	Yes	Yes	Yes	Yes	Yes
Type PC	No	No	No	No	No
Goal PC	Yes	Yes	Yes	Yes	Yes
Implementation Level FEs	Yes	Yes	Yes	Yes	Yes
Observations	476	476	476	476	476
R^2	0.661	0.679	0.665	0.671	0.661
Adjusted R^2	0.585	0.607	0.589	0.597	0.586
F Statistic (df = 20; 388)	37.888***	41.093***	38.432***	39.530***	37.904***

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Appendix C Implementation Level Table Output

Table C3 shows the output of Figure 4.

Table C3 Implementation Level

	Climate Vulnerability
	(1)
Town	−0.003
	(0.010)
Organization	0.021
	(0.043)
Tribe	−0.081**
	(0.038)
State	−0.012
	(0.011)
Poverty*	0.088***
	(0.016)
Unemployment*	0.161***
	(0.021)
Housing Burden*	−0.001
	(0.011)
Minority*	−0.013
	(0.010)
Single-Parent Household*	−0.012
	(0.019)
Mobile Homes*	0.070***
	(0.017)
ESL*	0.019
	(0.017)
Feature PC	Yes
Type PC	Yes
Goal PC	Yes
Implementation Level FEs	No
Observations	476
Total Sum of Squares	22.862
Residual Sum of Squares	7.7061
R^2	0.66293
Adjusted R^2	0.58305
F Statistic (df = 24; 384)	31.4674***

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Appendix D Policy Goal Table Output

Table D4 shows the output of Figure 5.

Table D4 Policy Goal

	Policy Goal				
	(1)	(2)	(3)	(4)	(5)
Extreme Heat	0.015**				
	(0.007)				
Flooding		0.010*			
		(0.006)			
Saltwater Intrusion			−0.018		
			(0.019)		
Sea Level Rise				0.012***	
				(0.004)	
Storm Surge					0.016***
					(0.006)
Poverty*	0.087***	0.086***	0.086***	0.090***	0.087***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment*	0.171***	0.176***	0.175***	0.167***	0.165***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Housing Burden*	0.002	0.003	0.002	0.0001	0.0001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Minotiry*	−0.010	−0.011*	−0.010	−0.011*	−0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Single Parent Household*	−0.012	−0.010	−0.011	−0.014	−0.016
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mobile Homes*	0.067***	0.066***	0.066***	0.068***	0.069***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ESL*	0.020*	0.020*	0.021*	0.019*	0.020*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Feature PC	Yes	Yes	Yes	Yes	Yes
Type PC	Yes	Yes	Yes	Yes	Yes
Goal PC	No	No	No	No	No
Implementation Level FEs	Yes	Yes	Yes	Yes	Yes
Observations	476	476	476	476	476
R^2	0.657	0.656	0.654	0.661	0.660
Adjusted R^2	0.580	0.579	0.577	0.585	0.584
F Statistic (df = 20; 388)	37.153***	36.990***	36.694***	37.850***	37.696***

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

662 # Appendix E Random Effects Robustness Tables

663 Table E5-E8 shows the output of the Random Effects models.

Table E5 Random Effects: Policy Features

	Climate Vulnerability				
	(1)	(2)	(3)	(4)	(5)
Economic Resilience	0.004 (0.006)				
Ecosystem Natural Resources		−0.004 (0.005)			
Government Bylaws			−0.013** (0.006)		
Infrastructure Built				−0.007 (0.005)	
Social Environmental Justice					0.014* (0.008)
Poverty*	0.087*** (0.011)	0.087*** (0.011)	0.088*** (0.011)	0.088*** (0.011)	0.087*** (0.011)
Unemployment*	0.161*** (0.021)	0.162*** (0.020)	0.165*** (0.020)	0.161*** (0.020)	0.158*** (0.020)
Housing Burden*	−0.002 (0.009)	−0.002 (0.009)	−0.001 (0.009)	−0.001 (0.009)	−0.002 (0.009)
Minority*	−0.013** (0.006)	−0.012** (0.006)	−0.013** (0.006)	−0.012* (0.006)	−0.012* (0.006)
Single Parent Household*	−0.013 (0.014)	−0.014 (0.014)	−0.011 (0.014)	−0.012 (0.014)	−0.015 (0.014)
Mobile Homes*	0.071*** (0.012)	0.071*** (0.012)	0.069*** (0.012)	0.070*** (0.012)	0.072*** (0.012)
ESL*	0.019 (0.012)	0.019 (0.012)	0.019 (0.012)	0.019 (0.012)	0.019 (0.012)
Feature PC	No	No	No	No	No
Type PC	Yes	Yes	Yes	Yes	Yes
Goal PC	Yes	Yes	Yes	Yes	Yes
Implementation Level FEs	Yes	Yes	Yes	Yes	Yes
Observations	476	476	476	476	476
R^2	0.662	0.662	0.665	0.663	0.664
Adjusted R^2	0.585	0.585	0.589	0.586	0.587
F Statistic (df = 21; 387)	36.020***	36.084***	36.631***	36.230***	36.397***

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Table E6 Random Effects:Plan Types

	Climate Vulnerability				
	(1)	(2)	(3)	(4)	(5)
Adaptation Plan	−0.002				
	(0.009)				
Case Study		−0.039***			
		(0.013)			
Mitigation Document			0.045**		
			(0.020)		
Disaster Recovery Plan				0.340***	
				(0.096)	
Resilience Plan					−0.003
					(0.006)
Poverty*	0.108***	0.107***	0.108***	0.103***	0.108***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Unemployment*	0.180***	0.180***	0.180***	0.180***	0.180***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Housing Burden*	0.006	0.006	0.006	0.005	0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Minority*	−0.006	−0.007	−0.005	−0.006	−0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Single Parent Household*	−0.0003	0.004	−0.001	0.001	0.001
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mobile Homes*	0.021**	0.016	0.022**	0.025**	0.021**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ESL*	0.017	0.014	0.018	0.017	0.017
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Baseline Climate Exposure	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Feature PC	Yes	Yes	Yes	Yes	Yes
Type PC	No	No	No	No	No
Goal PC	Yes	Yes	Yes	Yes	Yes
Implementation Level FEs	Yes	Yes	Yes	Yes	Yes
Observations	476	476	476	476	476
R^2	0.642	0.648	0.646	0.652	0.642
Adjusted R^2	0.625	0.632	0.629	0.635	0.626
F Statistic	814.239***	836.413***	827.784***	848.984***	815.083***

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Table E7 Random Effects: Implementation Level

	Climate Vulnerability
	(1)
Town	−0.005
	(0.006)
Organization	−0.016
	(0.040)
Tribe	−0.090**
	(0.040)
State	−0.010
	(0.008)
Poverty*	0.109***
	(0.015)
Unemployment*	0.178***
	(0.023)
Housing Burden*	0.005
	(0.010)
Minority*	−0.007
	(0.009)
Single Parent Household*	0.002
	(0.019)
Mobile Homes*	0.021*
	(0.011)
ESL*	0.017
	(0.018)
Baseline Climate Exposure	−0.001
	(0.002)
Feature PC	Yes
Type PC	Yes
Goal PC	Yes
Implementation Level FEs	No
Observations	476
Total Sum of Squares	29.826
Residual Sum of Squares	10.61
R^2	0.64427
Adjusted R^2	0.62451

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Table E8 Random Effects: Policy Goal

	Policy Goal				
	(1)	(2)	(3)	(4)	(5)
Extreme Heat	0.011*				
	(0.007)				
Flooding		0.003			
		(0.005)			
Saltwater Intrusion			−0.010		
			(0.015)		
Sea Level Rise				0.007**	
				(0.003)	
Storm Surge					0.007
					(0.005)
Poverty*	0.107***	0.108***	0.107***	0.110***	0.109***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Unemployment*	0.185***	0.189***	0.189***	0.179***	0.182***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Housing Burden*	0.006	0.006	0.006	0.006	0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Minority*	−0.005	−0.006	−0.005	−0.005	−0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Single Parent Household*	0.001	0.001	0.001	0.0005	−0.001
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mobile Homes*	0.017*	0.017*	0.018*	0.018*	0.019*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ESL*	0.018	0.020*	0.020*	0.018	0.018
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Baseline Climate Exposure	−0.002	−0.002	−0.002	−0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Feature PC	Yes	Yes	Yes	Yes	Yes
Type PC	Yes	Yes	Yes	Yes	Yes
Goal PC	No	No	No	No	No
Implementation Level FEs	Yes	Yes	Yes	Yes	Yes
Observations	476	476	476	476	476
R^2	0.642	0.640	0.640	0.643	0.641
Adjusted R^2	0.626	0.623	0.623	0.627	0.624
F Statistic	815.497***	806.124***	806.609***	818.986***	810.211***

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Appendix F PC Control Variable Robustness

Table F9 shows the output of Figure 13.

Table F9 Principal Component Socio-economic & Climate CVs

	Climate Vulnerability				
	(1)	(2)	(3)	(4)	(5)
Economic Resilience	0.003				
	(0.006)				
Ecosystem Natural Resources		−0.003			
		(0.005)			
Government Bylaws			−0.015**		
			(0.006)		
Infrastructure Built				−0.007	
				(0.005)	
Social Environmental Justice					0.012
					(0.008)
Adaptation Plan	0.002				
	(0.011)				
Case Study		−0.080***			
		(0.016)			
Mitigation Document			0.041*		
			(0.023)		
Disaster Recovery Plan				0.365***	
				(0.118)	
Resilience Plan					−0.002
					(0.006)
Town	−0.003				
	(0.010)				
Organization		0.027			
		(0.043)			
Tribe			−0.085**		
			(0.036)		
State				−0.010	
				(0.011)	
Extreme Heat	0.014*				
	(0.007)				
Flooding		0.011**			
		(0.006)			
Saltwater Intrusion			−0.020		
			(0.020)		
Sea Level Rise				0.012***	
				(0.004)	
Storm Surge					0.015**
					(0.006)
PC CVs	Yes	Yes	Yes	Yes	Yes
Policy PC CVs	Yes	Yes	Yes	Yes	Yes

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.

Appendix G Bivariate Robustness Output

Table G10 shows the output of Figure 14.

Table G10 Bivariate Robustness (No CVs)

	Climate Vulnerability				
	(1)	(2)	(3)	(4)	(5)
Economic Resilience	0.025*** (0.008)				
Ecosystems Natural Resources		−0.005 (0.007)			
Government Bylaws			−0.008 (0.009)		
Infrastructure Built				−0.005 (0.008)	
Social Environmental Justice					0.031*** (0.012)
Adaptation Plan	−0.011 (0.016)				
Case Study		−0.155*** (0.022)			
Mitigationd Document			0.043 (0.034)		
Disaster Recovery Plan				0.474*** (0.172)	
Resilience Plan					−0.008 (0.009)
Town	−0.021** (0.010)				
Organization		0.037 (0.048)			
Tribe			−0.094* (0.048)		
State				−0.038*** (0.012)	
Extreme Heat	0.027** (0.011)				
Flooding		0.013 (0.008)			
Saltwater Intrusion			−0.012 (0.029)		
Sea Level Rise				0.021*** (0.006)	
Storm Surge					0.041*** (0.008)
Policy PC CVs	Yes	Yes	Yes	Yes	Yes

Note: *Variable** indicates logged values; Significance levels are *p<0.1; **p<0.05; ***p<0.01.